# Applying tDCS over the Dominant Hemisphere to Observe Event-Related Desynchronization

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A thesis submitted to the Department of Computer Science and Engineering
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# Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

# Approval

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# Abstract

Although keeping us alive is arguably the most important function of the human brain, the human brain is responsible for a host of functions—including processing of environmental stimuli. Electroencephalography (EEG) is a psychophysiological technique used to measure electro-cortical activity in the brain. It is a noninvasive technique that provides a direct measure of the brain's electrical activity through placement of electrodes on the scalp which is quite precise and instantaneous. A set of probes or electrodes are placed on the scalp which receive EEG signals or brain waves. Using EEG signals we may analyze the mechanisms behind language, cognition, sensory functions, and brain oscillations. After gathering the eeg signals, it can be used as a neurofeedback - a process by which eeg signals are again applied to the brain with the same electrodes. By applying neurofeedback of some specific pattern or feature we can enhance those features and reduce the other features. Transcarnial Direct Current Stimulation (tDCs) is also another non-invasive method of neuromodulation which is used to constatly apply a small amount of electric current on the head with the use of electrodes. With adequate amount of training with neurofeedback, tdcs individuals may learn to control their own brain waves and thus changing their state of self at will. We have initiated a system where we use EEG-based neurofeedback and tDCs on the left hemisphere of the brain and observe Event-related desynchronization occuring on the right hemisphere. After applying five-fold cross validation method of classification we acquired an accuracy of 86.67% for anodal stimulation and 88.33% for cathodal stimulation.

**Keywords:** EEG, tDCS, Neurofeedback, Cognitive Load Index, Time-Frequency distribution features, Band extraction, ERD.

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# Table of Contents

# List of Figures

# List of Tables

# Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

*BCI* Brain Computer Interface

*CLI* Cognitive Load Index

*EEG* Electroencephalogarphy

*ERD* Event-Related Desynchronisation

*ERS* Event-Related Synchronisation

*FFT* Fast Fourier Transform

*ROC* Receiver Operating Characteristic

*tDCS* Transcranial Direct Current Stimulation

# Chapter 1

# Introduction

In this thesis we have tried to emphasize and hopefully contribute to the field of Bioinformatics. We went through some of the popular and latest research on brain-waves, EEG, neurofeedback, tDCS, classification techniques which is happening around the globe to find motivation and reason to do our thesis. Our whole research motivation will be explained with proper references through out this whole report.

## 1.1 Motivation

### 1.1.1 EEG

The electroencephalogram, or EEG, is an exemplary technique for estimating an individual's brainwaves. Terminals are set on the scalp and distinguish the miniaturized scale Volt estimated signals that outcome outside the head because of the synchronized neuronal activity inside the cerebrum [9]. Using electrical signals, their data is being processed by the neurons inside human cortex and activates the electrical recording of their activity, the electroencephalogram (EEG) [40]. A mobile EEG device by EMOTIV is shown in In Fig. 1.1 [34]. Brain responses to transcranial magnetic stimulation (TMS) recorded by electroencephalography (EEG) are emergent noninvasive markers of neuronal excitability and effective connectivity in humans. However, the underlying physiology of these TMS-evoked EEG potentials (TEPs) is still heavily underexplored, impeding a broad application of TEPs to study pathology in neuropsychiatric disorders [25] [21].


Figure 1.1: A Mobile EEG device.

### 1.1.2 Neurofeedback

Neurofeedback is a sort of biofeedback, which encourages restraint of mind capacities to subjects by estimating cerebrum waves and giving a remarkable signal. Neurofeedback normally gives the sound or potentially video analysis. Positive or negative input is created for alluring or bothersome cerebrum exercises, individually.Neurofeedback is certifiably not another idea. It has been the subject of the investigation of specialists for a very long while. Neurofeedback is a strategy that helps subjects to control their mind waves deliberately. Truth be told, the electroencephalogram (EEG) is recorded during the neurofeedback treatment. At that point, its different segments are removed and encouraged to subjects utilizing on the web input circle as sound, video or their mix. In like manner, electrophysiological parts are independently illustrated. As an outline, the intensity of a sign in a recurrence band can be appeared by a shifting visual diagram. During this methodology, the subject gets mindful of the progressions happening during preparing and will have the option to evaluate his/her advancement so as to accomplish ideal execution. For example, the subject attempts to improve the mind designs dependent on the progressions that happen in the sound or film.

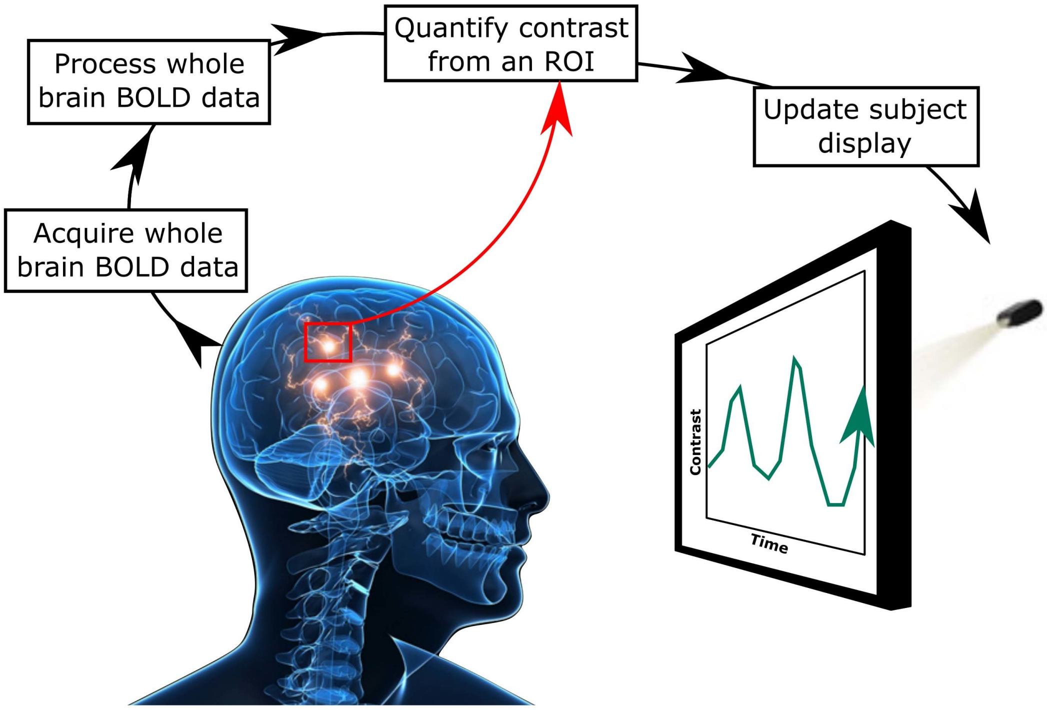


Figure 1.2: How Neurofeedback works.

Neurofeedback treatment conventions for the most part center around the alpha, beta, delta, theta, and gamma treatment or a mix of them, for example, alpha/theta proportion, beta/theta proportion, and so forth. Be that as it may, the most usually utilized conventions are alpha, beta, theta, and alpha/theta proportion. In this audit paper, we talked about different specialized and clinical subtleties of various neurofeedback treatment conventions. Until now, numerous researches have been led on the neurofeedback treatment and its viability on the treatment of numerous sicknesses. In Fig. 1.2 a general method of how neurofeedback is applied has been shown [23]. Neurofeedback, as different medications, has its very own advantages and disadvantages. In spite of the fact that it is a non-obtrusive methodology, its legitimacy has been addressed as far as decisive logical proof. For instance, it is costly, tedious and its advantages are not durable. Likewise, it may take a very long time to show the ideal enhancements. Nevertheless, neurofeedback is called as a reciprocal and elective treatment of many brain dysfunctions. Anyhow, modern studies does not consider incontestable results of its usefulness [20].

### 1.1.3 Transcranial Direct Current Stimulation

Transcranial direct current stimulation(tDCS) is a popular brain stimulation method that is used to modulate cortical excitability, producing facilitatory or inhibitory effects upon a variety of behaviors. There is, however, a current lack of consensus between studies, with many results suggesting that polarity-specific effects are difficult to obtain [24]. Fig. 1.3 shows six standard tDCS configurations [17].

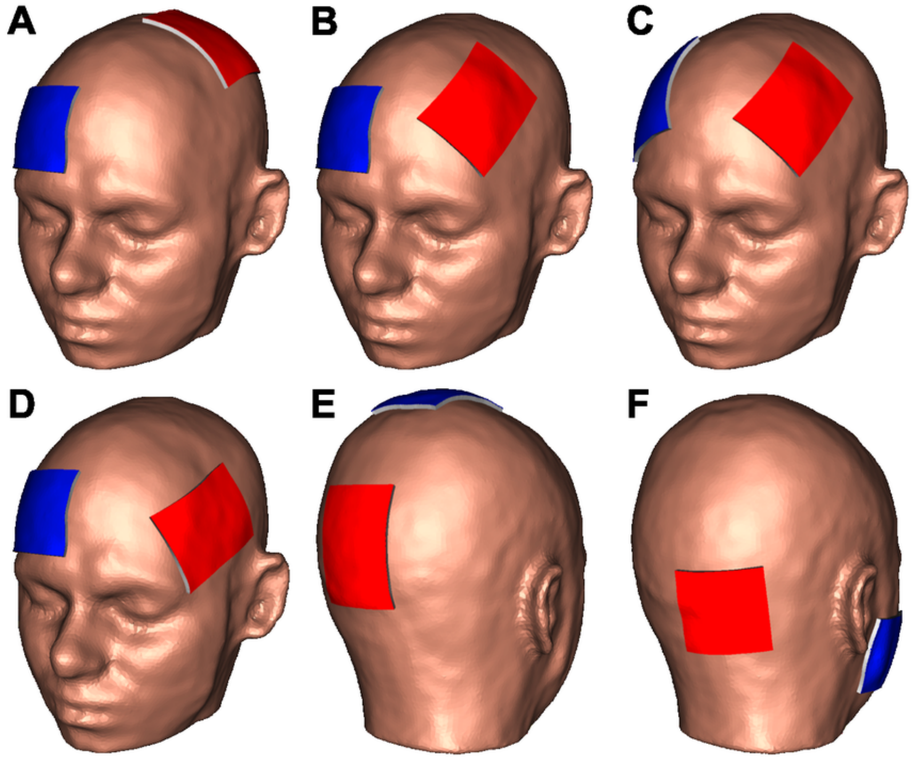


Figure 1.3: Six standard tDCS configurations.

tDCS is a non-invasive method, allowing for the reversible modulation of activity in particular brain regions. This has provided a valuable tool for establishing brain-behavior relationships across a variety of cognitive, motor, social, and affective domains and, in healthy populations, it has been shown to temporarily modify behavior, accelerate learning, and boost task performance. For example, anodal stimulation has been shown to enhance facial expression recognition or inhibit aggressive responses, whereas cathodal stimulation has been shown to foster implicit motor learning when stimulating the dorsolateral prefrontal cortex by suppressing working memory activity . In practical terms, the equipment is reusable, relatively inexpensive, and easily replaced if worn or damaged [3].

The region of interest is stimulated using the target electrode, the location of which depends on the hypothesis and task. For example, if the hypothesis concerns aggression, one might focus stimulation on the prefrontal cortex [13]. Tasks should be expected to recruit neurons in the target region, in order to observe stimulation-related changes in behavior. Bihemispheric montages (also known as "dual" stimulation) may instead be used whereby the positioning of both target electrodes is important for down-regulating one area (cathodal current) and up-regulating (anodal current) the parallel area in the opposite hemisphere. For example, if the hypothesis concerns motor outputs, one might focus dual stimulation to both motor cortices. It is just as important in these set-ups that the target regions are recruited for the task at hand [10].

The target region should be on the cortical surface, as scalp electrodes do not penetrate deep brain regions. Modeling studies have demonstrated that the distribution of the current can vary across subjects, even when the electrode montage is kept consistent, due to anatomical features such as skull thickness and composition [18]. Current direction may also be influenced by lesions that may be common in clinical samples. Use of neuro-navigational software allows the experimenter to more accurately place electrodes above a defined cortical location, whilst taking anatomical differences across participants into account. However, researchers should be aware that no matter what method of cortical localization (see section Localizing Electrode Placement) is used, surrounding regions may receive stimulation, potentially causing unspecified changes to task performance [12].

Sham tDCS acts as a control condition, in which a few seconds of stimulation at the start and the end of the programmed time period is administered to a participant in order to mimic cutaneous perceptions (e.g., itching, tingling) that tend to be reported within the first few moments of the stimulator being switched on [6].

## 1.2 Major Contribution

Just after the tests, we gave each participant a questionnaire on side-effects to determine how their physical experiences of tDCS varied. This supports the view that tDCS results over EEG are not due to physical feeling related with actual stimulation if discrepancies between real and sham stimulation are not observed. The survey invited participants to assess on a discreet 1-5 scale the intensity of physical perceptions of stimulation. More details can be found elsewhere on the query naire [16]. Because the data did not match a standard division, the Mann-Whitney U test was used for comparison.

## 1.3 Thesis Orientation

The goal of this research was to check whether the contralateral tDCS could have interhemispheric effects on the spectral energy of the non-stimulated hemisphere, and whether these effects could be used to improve the strength of the ERD in the sense of a neurofeedback-guided motor imaging model of neurorehabilitation. Our initial hypothesis was that tDCS could take advantage of interhemispheric inhibition, i.e. that contralateral cathodal stimulation could lead to ERD facilitation on the unstimulated hemisphere, whereas contralateral anodal stimulation could result in inhibition. As addressed more specifically in Section 1.1.3, our study of ERDs has not validated our theory of cathodal stimulation at least: our results suggest in general that while contralateral ERDs are decreased during anodal stimulation, symmetrical stimulation does not occur. Although results of ERD suggest contralental tDCS are not applicable to rehabilitation, the impact of the two stimulation polarities on cortical rhythms in the unstimulated hemisphere has been shown in a spectral power analysis. The spectropower discussion reinforced and concludes the previous ERD debate, indicating that the influence on the non-stimulated hemisphere will affect not only anodal, cathodal tDCS.

# Chapter 2

# Literature Review

Neurofeedback setting utilize recording data method via EEG. BCI (Brain computing interface) applications has the ability to communicate with external devices, such as computers. NFB training can result in brain plasticity through a reinforcement learning process. NFB-evoked plasticity can be employed to treat neurological disorders; this is an alternative to pharmacological treatment and cognitive enhancement therapy. Thus, EEG-based BCIs can be used for neurorehabilitation of alzheimer patients [39].

Proposing a trainability of alpha neurofeedback training in terms of changes in both alpha amplitude and alpha duration. 50 healthy participants who were randomly assigned to a group (based on age) receiving a 8-12 Hz amplitude (Alpha) training and a group (based on gender) receiving a random training with frequencies to manipulate ranging from 7 to 20 Hz for control group. All subjects conducted several neurofeedback training sessions per week over a period of 4 weeks. Working memory was assessed using standard tests in order to test whether working memory changes as a consequence of the neurofeedback training where as the control group had no change in alpha amplitude and duration. The Alpha training group showed a progressive, significant increase in the alpha amplitude and total alpha duration of the frontoparietal region [19].

In the paper published by Vernon et al(2005), it was concluded that the purpose of neurofeedback is to increase efficiency of trainees and to reduce the amount of mistakes they regularly do. EEG neurofeedback can affect neuro cortical activity and make changes to it by influencing - sport, cognitive performance and artistic performance. For our research we are only considering the alteration of cognitive performance using EEG neurofeedback. The aim of the paper by Vernon is to show that people can learn to control their own neuro- cortical activity by previously training with neurofeedback. We can utilise this by training some alzheimer patients with proper neurofeedback and later on observe if their condition is going for betterment with fewer memory problems and increase efficiency while remembering trivial information. For this process to work, we need to figure out the relation between a particular brain frequency and loss of memory. It should be stated that, Vernon already showed that theta waves (4-8 hz) are responsible for memory functions. This information makes it easy for us to find features that can help enhance memory of an alzheimer patient [41].

Cotelli said in their paper that the aim of their present study in the field of brain study using BCI is to investigate the effects of anodal tDCS (AtDCS) combined with memory training on face-name associations in an AD patient sample. Their study comprised of thirty six Alzheimer disease patients who were randomly assigned to one of three study groups: Group 1, AtDCS plus individualized computerized memory training; Group 2, placebo tDCS plus individualized computerized memory training; Group 3, AtDCS plus motor training. The result of their study suggests that - a general improvement in performance was observed after 2 weeks of memory training. Both the anodal tDCS plus individualized computerized memory training and the placebo tDCS plus individualized computerized memory training groups had significantly improved performances at 2 weeks compared with the AtDCS plus motor training group. Therefore, to conclude they have added that their findings suggest a beneficial effect of individualized memory rehabilitation in Alzheimer Disease patients [14].

Clare, Wilson and Carter said in their paper - Relearning face-name associations in early Alzheimer's disease that Alzheimer Disease is a progressive disorder that affects several cognitive functions. However, some aspects of cognitive functions are preserved until later in the disease and can therefore be the targets of specific "rehabilitative/preservative" interventions [33].

In the paper Psychological compensation: a theoretical framework, authors have found that despite the memory deficits associated with AD, episodic memory can be enhanced when adequate support is provided [8]. Transcranial direct current stimulation generates an increase or a decrease in neuronal excitability that can modulate cognitive task performance by applying weak electrical currents directly to the head over a long period of time, usually on the order of minutes. tDCS delivers

a weak polarizing electrical current to the cortex through a pair of electrodes, and brain excitability can be increased via anodal stimulation (AtDCS) or decreased via cathodal stimulation (CtDCS) depending on the polarity of the current flow [7].
It has also been shown that a single tDCS session can ameliorate memory deficits in AD patients [10]. demonstrated that repeated sessions of anodal tDCS applied bilaterally over the temporal area led to an increase in performance of visual recognition memory tasks in a group of AD patients stable at a 4-week follow-up [11].

The aim of this study was to test whether contralateral tDCS could have interhemispheric effects on the spectral power of the unstimulated hemisphere, and whether such effect could be used to enhance ERD magnitudes in the context of a neurofeedback-guided motor imagery paradigm for neurorehabilitation. The analysis of ERDs did not confirm our hypothesis, at least in the case of cathodal stimulation: our results indeed suggest that, while contralateral ERDs are reduced during anodal stimulation, there is no symmetric facilitation for cathodal stimulation. Discussion on ERD, suggesting that not only anodal but also cathodal tDCS can impact the rhythms of the unstimulated hemi-sphere, although the effect is not task-specific.According to the Mann- Whitney U test, we found no differences in the side-effect scores between sham and real stimulations. This supports the view that the tDCS impact on the EEG rhythm is not just a placebo/somatosensory effect due to the physical perception of the Stimulation [36].

Noninvasive brain stimulation has developed as a promising tool for cognitive neuroscientists. The purpose of this paper is to review information on the use of TMS and tDCS as research tools to facilitate motor memory formation, motor performance and motor learning in healthy volunteers. Within the past two decades noninvasive brain stimulation has been used as a probe to modulate attention, memory, motor and language functions in humans. TMS and tDCS can enhance or decrease excitability in target cortical regions depending on the parameters of stimulation utilized.

Motor learning is associated with functional changes in a distributed network that includes the primary motor, premotor and supplementary motor cortices, the cerebellum, thalamic nuclei and the striatum. Most TMS and tDCS studies carried out so far to study the role of motor areas in motor learning have focused on M1. M1 is the encoding of elementary motor memory, adaptation, skill learning based on human neuroimaging studies, it was proposed that application of noninvasive stimulation with parameters that enhance motor cortical excitability could secondarily facilitate motor learning.

While the previous paragraphs depict a relatively consistent and homogenous picture on the effects of up- and down-regulation of excitability within M1 on motor learning and motor memory formation, several caveats should be kept in mind. First, induction of a virtual lesion or enhancement of activity in one cortical area may result in behavioral changes through specific effects on that area or secondarily through distant effects on other interconnected cortical areas. This phenomenon, referred to as homeostatic plasticity or metaplasticity and discussed elsewhere, may potentially impact motor learning [8].

Pfurtscheller, Neuper, & Mohl (1994) in their paper Event-related desynchronization (ERD) during visual processing, have mentioned that the short-term attenuation or blocking of rhythms in the alpha (Beta-band) is event-related (ERD). During but also prior to visual stimulation, ERD is found. There are two different types of ERD: one shorter, more localized to occipital areas and with upper Alpha components; the other longer, broader, more prominent to parietal areas and more extensive to lower Alpha components. The first is most definitely the main visual processing and retrieval of information, the latter more related to cognitive processing and attention mechanisms [4].

In the paper published by Pfurtscheller (1977) said that, the activity with internal or external concentrations contributes to the event-related response (ERP) known as phase-locked and event-related synchronization (ERS) as well as to an event-related EEG response known as event-related desynchronization (ERD). All ERPs and ERD / ERS have different spatiotemporal patterns and can therefore be viewed as reactivity patterns of various neural systems. The alpha and beta band's ERD rhythms may be interpreted as correlates of the active neural structures and ERS as correlates of deactivated neural structures in an alpha and low beta band (< 30 Hz.). At the same time or at different times at the same spot, ERD and ERS can be located at various cortical locations, where an ERS can also react. Measurements within fraction of a second of ERD / ERS patterns can therefore be used for the study of cortical dynamics before, during and after sensory, motor or cognitive procedures. The dynamics of cortical processes in a time / space region are shown by observations of EROR / ERS in a voluntary movement phase, with significant influence from the frequency band [4]. He also identified a new method in his paper, Graphical display and statistical evaluation of event-related desynchronization (ERD) that it helps to quantify changes in the rhythmic effects of alpha during sensory stimulation that enables quantification of event-related desynchronization (ERD) [5].

In the paper, Functional mapping of human sensorimotor cortex with electrocorticographic spectral analysis. I. Alpha and beta event-related desynchronization, the authors have mentioned that Human scalp EEG experiments have shown that alpha (8-13 Hz) and beta (15-25 Hz) event-related desynchronization (ERD) can be used in the sensorimotor cortex functional activities. Nevertheless, somatotopy has not been studied in depth in most previous studies and short, self-serving gestures based on motor performance preparation have been used. During the optical decision task designed to enable the representation of different corps sections of the sensory motor cortex, we documented the electrocorticographic (ECoG) signal in five clinic subjects [2].

The authors of the paper, Single-session tDCS over the dominant hemisphere affects contralateral spectral EEG power, but does not enhance neurofeedback-guided event-related desynchronization of the non-dominant hemisphere's sensory motor rhythm, said that Our ability to influence neuroplastics has resulted in significant neurorehabilitation research from Transcranial Direct Current Stimulation(tDCS) and Neurofeedback led Motor Imaging(MI). As tDCS has shown that it modulates event-related desynchronisation(ERD), it is recently proposed to combine the neuronal signatures of the observed motor imaging to provide neurofeedback. One of the drawbacks of this method is that the region targeted at stimulation is the same as the neurofeedback signal. As tDCS may interfere with the electro-EEGs proximal.
tDCS is a noninvasive brain stimulation technique consisting of a pair of electrodes, at least one being mounted on the scalp, providing a low-intensity direct current of at least 1-2 mA in electrodes of 35cm2 for a limited time (10-20 minutes). tDCS causes polarity-dependent modulations of excitability with increased anodal stimulation and decreased cortical excitability. Cortical excitability modulation impacts neuroplasticity and can potentially boost engine recovery.

As for motor imagery (MI), its use in neurorehabitation was suggested due to the technique's ability, irrespective of its residual degree of engine control, to recruit roughly the same areas as open motion. The repeated activation of the MI learning motor system facilitates the neuroplasticity of the region and therefore increases recovery. Nevertheless, because engine imaging is a purely mental process it has been shown recently that better recovery outcomes can be obtained by a sophisticated brain computer (BCI) interface and in particular a neurofeed-back device, which closes the group with sufficient feedback.

The author also mentioned that in general, a BCI is a system that tracks and converts neural activity for a certain device into a control signal (e.g. robotic arm, chair, computer). In addition to being used for communications or command, BCIs have recently emerged in the context of neurorehabilitation, in which neurophysiological characteristics correlated with tentative motion or motor picture processing is used to provide users with input appropriately (neurofeedback) The neural signature of motor imagery is, on a cortical basis, event-related desynchronization (ERD) of sensorimotor rhythms (SMR) in the motor region contrary to motion. With ERD identification and conditional input, the BCI objective the participation of the power supplier and facilitates the optimal regulation of cortical rhythms and thus directs the exercise, while preserving the user's dedication and motivation.

Several studies have recently shown that tDCS can modulate ERD-induced motor imagery. The majority agree that the frequency of the ERD in the stimulated region increases with anodal stimulation and cathodal stimulation decreases. Anodal tDCS was thus proposed as a conditioning method to improve neurofeedback-guided MI workouts [36].

# Chapter 3

# Background Study

There were several processes involved in the research including - gathering the right data-set for related to our motivation of work, extracting different frequency bands from the gathered EEG signal, Labelling the extracted bands (ERD-ERS), extracting the time-frequency features using FFT (Fast Fourier Transform) and DWT (Discrete wavelet transform) and finally merging the above and classify the data using 5-fold cross validation in order to estimate the skill of the model on the data.

For collecting the data, we needed an EEG data-set which had both neurofeedback and tDCS applied on the volunteers. For this purpose we were interested in whether neurofeedback as well as tDCS had any significant effect on the brain as well as the brain-waves specially the alpha $(8-12hz)$ frequency band. In order to observe any changes in the brain-waves due to neurofeedback and tDCS we chose a metric which we thought would be the most appropriate - Event Related Desynchronization.

In favour of our research we had to go through bunch of different concepts before applying them as code in MATLAB. These concepts will be shared in the next few sections of this chapter.

## 3.1 Time-frequency distribution

In signal processing, time–frequency analysis comprises those techniques that study a signal in both the time and frequency domains simultaneously, using various time–frequency representations. Rather than viewing a 1-dimensional signal (a function, real or complex-valued, whose domain is the real line) and some transform (another function whose domain is the real line, obtained from the original via some transform), time–frequency analysis studies a two-dimensional signal – a function whose domain is the two-dimensional real plane, obtained from the signal via a time–frequency transform. Fig. 3.1 shows time domain and frequency domain side by side for reference [1].

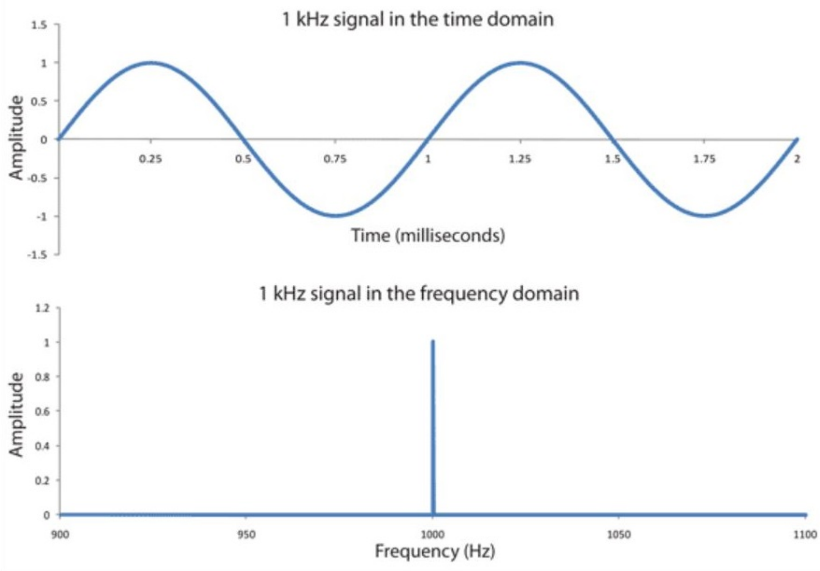


Figure 3.1: Time domain and frequncy domain.

The functions and their transform representation are often tightly connected, and they can be understood better by studying them jointly, as a two-dimensional object, rather than separately.

### 3.1.1 Fourier Transform

The Fourier Transform is a tool that breaks a waveform (a function or signal) into an alternate representation, characterized by sine and cosine. The Fourier Transform shows that any waveform can be re-written as the sum of sinusoidal functions. Virtually everything in the world can be described via a waveform - a function of time, space or some other variable. For instance, sound waves, electromagnetic fields, the elevation of a hill versus location, a plot of VSWR versus frequency, the price of your favorite stock versus time, etc. The Fourier Transform gives us a unique and powerful way of viewing these waveforms.

One of the fundamental Secrets of the Universe is that all waveforms, no matter what we observe in the universe, are actually just the sum of simple sinusoids of different frequencies. The Fourier Transform decomposes a waveform - basically any real world waveform, into sinusoids.

A fast Fourier transform (FFT) is an algorithm that computes the discrete Fourier transform (DFT) of a sequence, or its inverse (IDFT). Fourier analysis converts a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa. The DFT is obtained by decomposing a sequence of values into components of different frequencies.

### 3.1.2 Discrete Wavelet Transform

A signal can be decomposed into orthogonal wavelets if wavelet decomposition technique is used correctly. A representation of multi-resolution provides a simple hierarchical structure for analyzing the signal at different resolution rates. In terms of Fourier transform components or Walsh or Haar functions, this is analogous to the notion of decomposing a signal. Orthogonality is a special and complete signal representation. Based on Mallat theory, a signal's multi-resolution representation is effective in analyzing a signal's information content in different detail levels (Mallat, 1989). At a given resolution, this operator is able to approximate a signal. Each algorithm stage produces wavelets with sequentially finer signal content representation. To achieve an orthogonal wavelet representation, a given wavelet function, f(t), is first dilated by the $2j$ scale coefficient at a scaling index level equal to zero, then translated by $2jn$ and normalized by Eq. 3.1.

$$\sqrt{2^{-j}}\phi_{2j}(t - 2^{-j}n) \tag{3.1}$$

The algorithm starts with an $A2j$ operator for discrete signals that take a signal's projections, $f(t)$ to the $V2j$ orthogonal based on the Eq. 3.2.

$$A_{2j}f(t) = 2^{-j}\sum_{n=-\infty}^{\infty}(f(u), \phi_{2j}(u - 2^{-j}n))\phi_2 j(t - 2^{-j}n) \tag{3.2}$$

where the level of resolution is defined by $2j$. $A2j$ is known as a multi-resolution operator approximating a $2j$ resolution signal. Successively lower resolution signals can be obtained by repeated application of the operator A2j(-J≤j≤1), where J defines peak resolution so that $A2jf(x)$ is the closest approximation of function $f(x)$ at resolution $2j$. Doubechies wavelet transform is one of the most common form of DWT transforms used by multilevel decomposition methods to decompose a signal into its components. These wavelet transform resembles the Haar wavelets. Because of the similarity between these signals in calculating running averages and variations by scalar products of scaling signal and wavelets, there is a slight difference between these signals, due to the concept of scaling signal and wavelets. In case of Doubechies wavelet transform the scaling signals and wavelets has slightly longer supports, which means that they produce averages and differences using just a few more values from the original signal. Nevertheless, this small adjustment resulted in a huge increase in the current transform's capabilities. The number $N$ refers to the number of vanishing moments in Doubechies wavelet transform ($dbN$), meaning that by increasing the value of $N$ the sum of vanishing moment would take higher values correspondingly, resulting in a smoother wavelet and obtaining longer wavelet filters (Soman and Ramachandran, 2010). It should be known that, for wavelet $db2$ the wavelet length is $2*2 = 4$, for wavelet" $db3$ the wavelet length is $2*3 = 6$, and so on, the wavelet length is $2 * 3 = 6$. In the case of higher-order decompositions such as third-level decomposition, the sum of all third-level decomposition components (that is, third-level approximation and first-level detail) is returned to vector "$c$" and vector $l$ is the length of each element. Whereas, $s$ refers to the recorded signal [28]. Signal transformation into wavelets is shown in Fig. 3.2 [28].

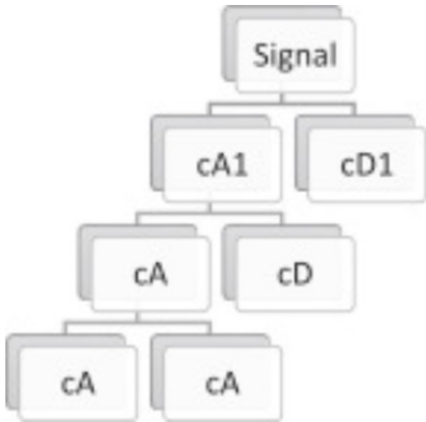


Figure 3.2: Signal transformation into wavelets.

Wavelet Transform is a frequency transform. In the same manner, Fourier Transform is also a frequency transformation, but with the Wavelet Transform, there are some significant differences. The most important difference is that while the Fourier Transform is defined on the spatial frequency domain, both the spatial frequency and spatial position characterize the Wavelet Transform.In other words, the Fourier Transform depends only on the spatial frequency, i.e. $FT(v)$, whereas the Wavelet Transform depends on the $v$ frequency and $t$ position, i.e. it can be written as a function of the form $WT(v, t)$. It means the Fourier Transform is telling us about the spatial frequencies in our image, but the Wavelet Transform is telling us about them and where they are in our image [37].

## 3.2 Brain wave bands

Brainwaves are electrical impulses in the brain. An individual's behavior, emotions, and thoughts are communicated between neurons within our brains. Brainwaves are produced by synchronised electrical pulses from masses of neurons communicating with each other. Brainwaves occur at various frequencies. Some are fast and some are slow. The classic names of these EEG bands are delta, theta, alpha, beta, and gamma. They are measured in cycles per second or hertz (Hz) [44]. The different EEG bands has been shown in Fig. 3.3 [38].

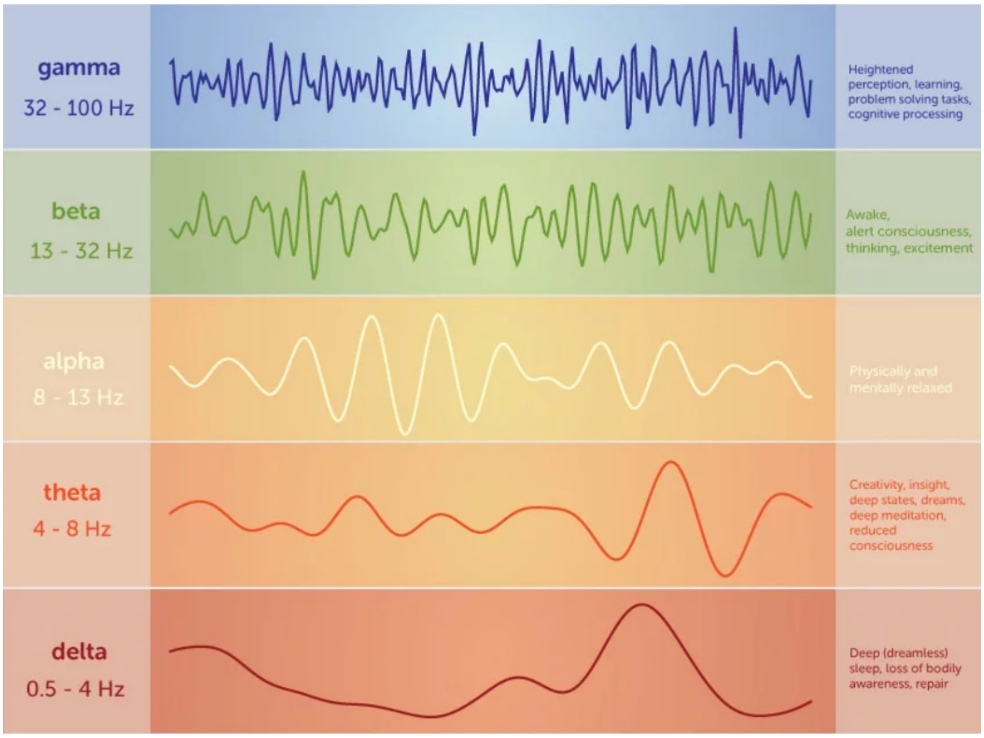


Figure 3.3: Brain wave bands of different frequency range.

**Delta brain waves (1-3 Hz)** are brain waves that are the lowest and highest amplitude and are the experience of sleeping. In general, the dominant brainwave states are associated with different levels of awareness. **The Theta brainwaves (4-7 Hz)** reflect a dreamy, expansive state of mind and are related to cognitive inefficiency. Theta brain wave activity at very slow rates is a very relaxed phase, reflecting the creeping area from waking to sleep. **Beta brainwaves (13 – 38 Hz)** are smaller, stronger brain waves connected to an externally centered state of mental, cognitive and concentration activity [44]. In Fig. 3.3, the different frequency bands generated in our brain along with their names and how they effect human behaviour is shown. **Alpha Waves (8-12 Hertz)** Alpha waves is more correlated with thoughts/ thinking/ creativity/ intelligence For verbal thoughts there is a decrease of alpha waves in LH(Left Hemisphere) For visual thoughts there is a decrease of alpha waves in RH(Right hemisphere) Creativity of an individual corresponds with lower mean alpha Index recorded from right Occipital parietal region, On the other hand more alpha activity showed good memory performers. Intelligence corresponds with alpha waves with higher amplitude For ease of study purpose, Alpha waves are divided into two groups : Lower Alpha Wave (7-9.5 hertz) (related to attentional processes)and Upper Alpha Wave (9.5-12 Hertz) (semantic memory process) Other research show Alpha waves should be divided into 6-8 hz, 8-10 hz and 10-12 hz Neurofeedback using Alpha waves has shown better short term memory [41].

Directly training a specific frequency component may make it easier to identify possible changes. Training participants to change their brain waves might be a better method of enhancement which will enable them to shift their electro-cortical activity within a particular hemisphere of the brain voluntarily. One dimensional wavelet decomposition occurs in the manner shown in Fig. 3.4 [43].

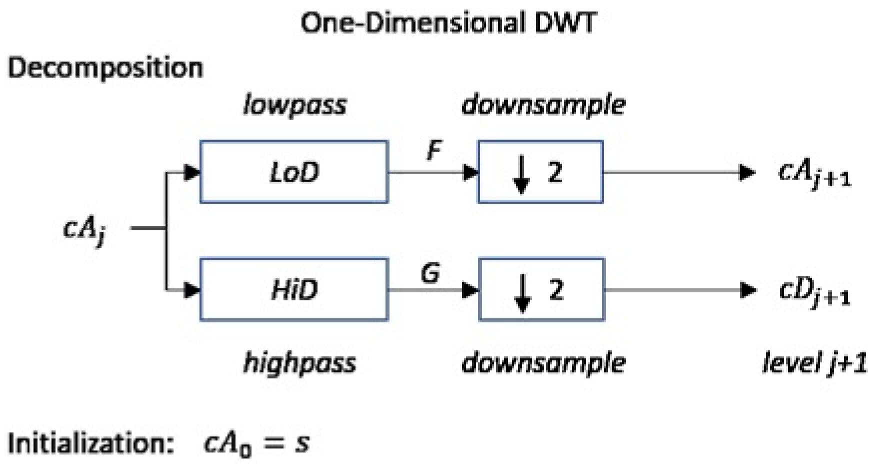


Figure 3.4: One dimensional wavelet decomposition.

## 3.3 Classification of data

Once we are finished with our design learning, we can't assume that the information you have not seen before will perform well. This implies that we can not be sure of the required precision and variability in the production environment of the prototype. We need some sort of assurance that our model's predictions are accurate. This requires our model to be validated. This process is called validation when it comes to determining whether the numerical results, which quantify the hypothesized relation between variables, are acceptable as data descriptions.

We need to test it on some unreported data to determine the quality of all machines learning models. We can say that our model is under-fit/ over-fit/ well-generated, based on unseen data performance. Cross validation (CV) is one of the techniques for evaluating the efficacy of machine learning systems. If we have limited data, CV is often re-sampling process used in the analysis of a system. With CVs, a sample/ part of information on which the model isn't used is to be kept away and this test/ validation sample should be used later.

We used k-fold cross-validation in this case. K-Fold is a common and understandable model, usually contributing to a less prejudicial model compared to other approaches. Because every observation from the original data-set is ensured in the training and test collection. If we have limited data entry, this is one of the best approach. The following steps are taken in this way [26].

1. We randomly divide the entire data into k folds (value of k is not too low or too high, but 5). The higher K value leads to a less inclined model (but large variance may lead to overfit, whereas the lower K value is comparable to the train split approach we saw previously).

2. We then connect K-1 folds to the template with the rest of the $Kth$ fold. The remaining $Kth$ folds are checked. We noticed the effects/ errors.

3. Repeat it until the function is described by each K-fold. And take the average of our values. This will be the model's performance metric.

# Chapter 4

# Proposed Model

In this chapter we will talk about the approach to validating that ERD occurs while applying tDCS to the brain. The steps are in the most basic form acquiring a proper data-set, band extraction and then labelling the data-set using cognitive load index, extracting time-frequency features and finally classifying the proposed model. The work-flow of our proposed model has been given in Fig. 4.1.

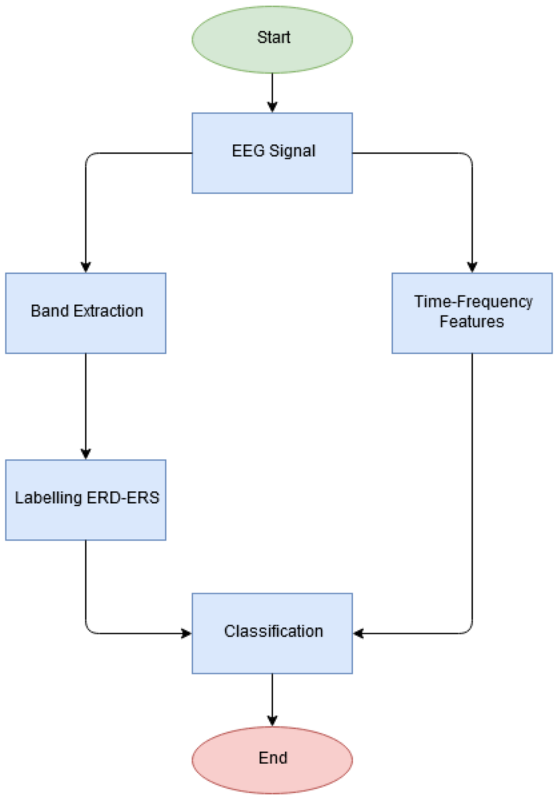


Figure 4.1: Work-flow diagram.

## 4.1 Dataset

The dataset that we have gathered has been arranged systematically. The EEG data was gathered for this research from twenty healthy volunteers. The participating volunteers in the research are firstly grouped according to the type of stimulation they received - anodal or cathodal stimulation. These EEG data was collected from the right motor cortex of the brain. The location of 12 EEG recording sites, location of the ground electrode and the two stimulation electrodes has been shown in Fig. 4.2 [36]. In the meantime participants left-hand motor imagery which is collected before, during and after applying contralateral tDCS on their dominant hemisphere. Inside each folder, data are organized according to the subject (S01, S02... to S10). Inside every subject folder resources are divided according to experiment day1 and day2. Among them one corresponding to the real one and another one corresponding to the sham one [30].

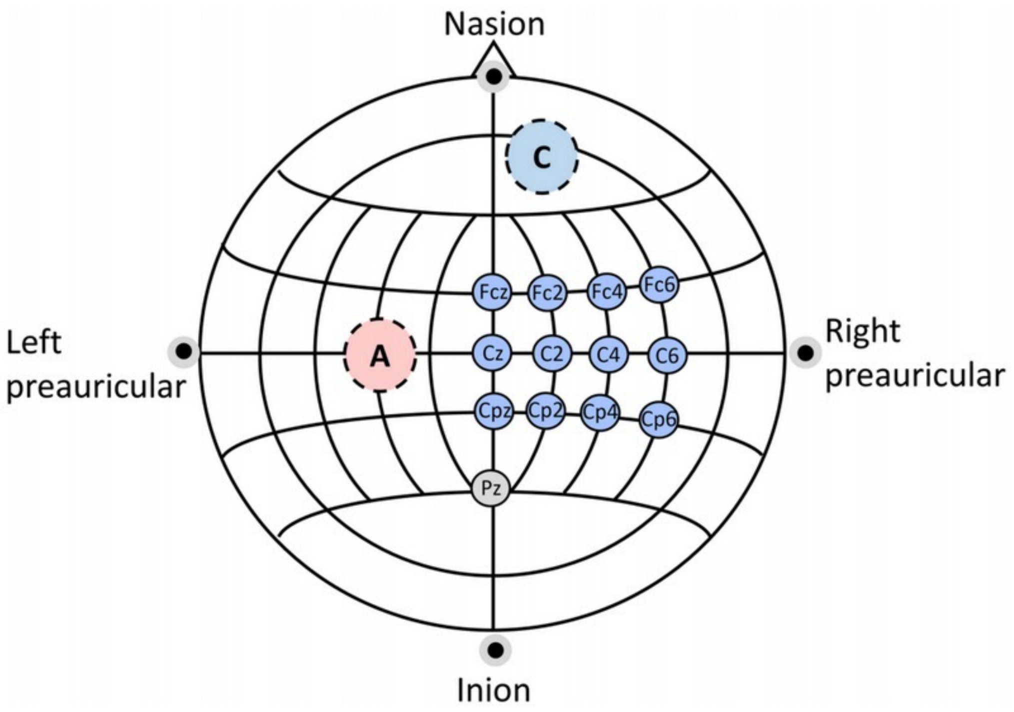


Figure 4.2: Location of the twelve EEG recording sites (right hemisphere), the ground electrode (Pz) and the two stimulation electrodes (anodal stimulation in this example).

Each day was composed by 15 runs of brain computer interface (BCI) operation with feedback (neurofeedback01, neurofeedback02, neurofeedback03... to neurofeedback15). Runs 01-05 correspond to the condition "before", runs 06-10 to the condition "during" and runs 11-15 to the condition "after" tDCS. The dataset also includes the calibration runs (calibration01, calibration02...), collected at the beginning of the first experimental day 1. Each "neurofeedback" or "calibration" folder finally contains a ".txt file", which includes: the EEG raw data collected from all twenty individuals in the corresponding run from the 12 EEG electrodes used in the study, the reference signal from right ear lobe and an additional column indicating the trial condition (rest, ready, motor imagery and rest).

### 4.1.1 EEG data

Data are collected at 128Hz and stored as arrays in text format files with rows as specimens and columns as channels. There are 12 EEG channels in the 12 first lines, which are registered by the ground electrode at pz. [Fcz Fc2 Fc4 Fc6 Cz C2 C4 Cpz Cp2 Cp4 Cp6]. Fig. 4.3 shows the experimental stimulation condition of all participants [36]. The 13th column includes the right ear lobe reference signals. In the 14th line, data on the test situation is given, in particular:

1. "0" for samples in the "rest" period before the warning tone (lasting 2s)
2. "1" for samples in the "ready" period after the warning sound and before motor imagery (lasting 1s)
3. "2" for samples in the "motor imagery" period (4s during calibration, or up to 8s during neurofeedback)
4. "3" for samples in the "rest" period concluding the trial (lasting 5s)

| CATHODAL GROUP | | | ANODAL GROUP | | |
|---|---|---|---|---|---|
| **Subject** | **Day1** | **Day2** | **Subject** | **Day1** | **Day2** |
| $S_{01}$ | Cathodal | Sham | $S_{01}$ | Sham | Anodal |
| $S_{02}$ | Sham | Cathodal | $S_{02}$ | Sham | Anodal |
| $S_{03}$ | Sham | Cathodal | $S_{03}$ | Anodal | Sham |
| $S_{04}$ | Sham | Cathodal | $S_{04}$ | Anodal | Sham |
| $S_{05}$ | Cathodal | Sham | $S_{05}$ | Sham | Anodal |
| $S_{06}$ | Cathodal | Sham | $S_{06}$ | Anodal | Sham |
| $S_{07}$ | Sham | Cathodal | $S_{07}$ | Anodal | Sham |
| $S_{08}$ | Cathodal | Sham | $S_{08}$ | Sham | Anodal |
| $S_{09}$ | Sham | Cathodal | $S_{09}$ | Sham | Anodal |
| $S_{10}$ | Cathodal | Sham | $S_{10}$ | Anodal | Sham |

Figure 4.3: Experimental day stimulation condition of all volunteers.

## 4.2 Time-Frequency features

### 4.2.1 Wavelet packet decomposition

In case of deriving the time-frequency features we had to use the one dimensional Wavelet packet decomposition function.The wavelet packet approach is a wavelet decomposition generalization which gives a finer interpretation of the signal. Wavelet packet atoms are waveforms that are indexed by three natural parameters: location, scale as in the decomposition of the wavelet, and frequency [42].

In the MATLAB code given in Eq. 4.1, "$data11$" is a vector which is decomposed to the level "N = 3" using the wavelet specified by "Shannon".

$$wpt = wpdec(data11, 3,' db1',' shannon'); \tag{4.1}$$

### 4.2.2 Fast Fourier Transform

The decomposed waveform from the wpdec function is then fed to an $fft$ function to get the features for our research. the $fft$ function uses a Fast Fourier Transform (FFT) algorithm to compute X's discrete Fourier Transform (DFT). The MATLAB code for usage of fft in our thesis has been given in Eq. 4.2.

$$\begin{gathered} dread = read(wpt,' data'); \\ F = fft(dread); \\ pow = F. * conj(F); \\ f2 = sum(pow); \\ F = fft(data11); \\ pow = F. * conj(F); \end{gathered} \tag{4.2}$$

Here the output from the use of function *wpdec* is saved in a variable named dread which is then used as a parameter of the the function $fft$ and saved in a variable $F$. $f2$ and $f3$ are used to store the results after using the fft function.

## 4.3 Band Extraction and Labelling

### 4.3.1 1-D wavelet decomposition

Wavelet decomposition is one of the most crucial part of the band extraction process as it is used for multilevel one-dimensional wavelet analysing. Wavedec is one of the functions of the Wavelet toolbox in MATLAB which can be used either as a wavelet decomposition tool as a low cut filter and high cut filter or it can be used for wavelet analysis using a specific wavelet. The output decomposition structure consists of the wavelet decomposition vector c and the bookkeeping vector l, which contains the number of coefficients by level. The structure is organized as in this level-3 decomposition diagram [43]. Fig. 4.4 shows how 1-D wavelet decomposition happens [43].

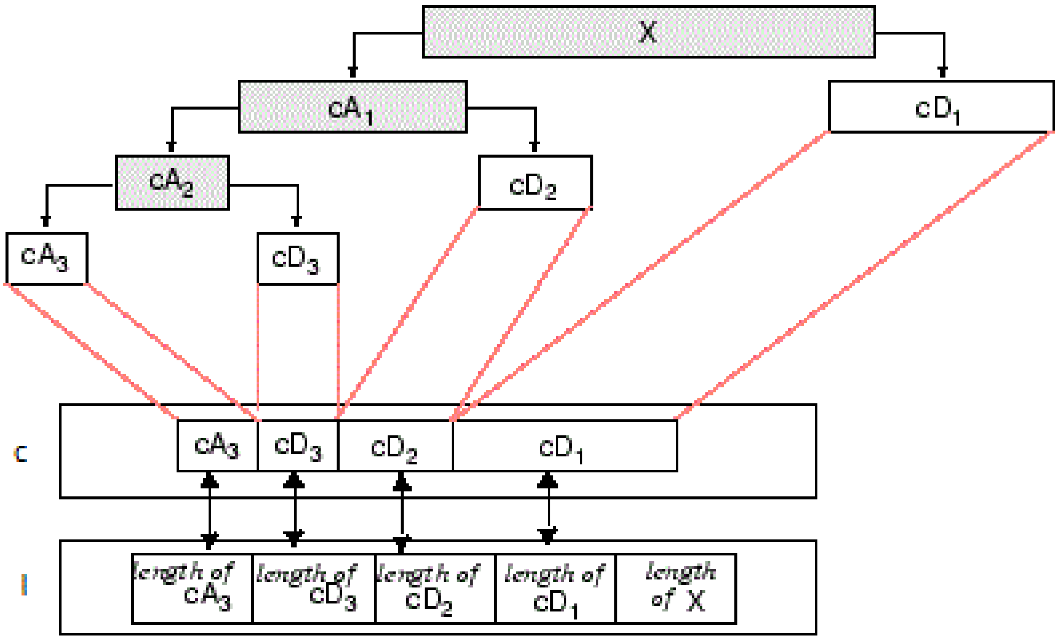


Figure 4.4: One dimensional wavelet decomposition .

In our case it has been used primarily for the band extraction purpose specifically the alpha band, which can be used later for labelling. Eq. 4.3 shows the MATLAB code with which we have used the wavedec function to do the 1-D wavelet decomposition.

$$[C, L] = wavedec(mySignal, 7, waveletFunction); \tag{4.3}$$

### 4.3.2 1-D wavelet coefficients

For the purpose of reconstructing single branch from 1-D wavelet coefficients we had to use wrcoef function which is another function of the Wavelet toolbox from MATLAB. The wrcoef function is used for reconstructing the coefficients of a one-dimensional signal given the wavelet decomposition structure (C and L) and either the specified wavelet (for more detail, see wfilters) or the necessary reconstruction filters (Lo R and Hi R) [32]. Reconstruction of single branch from one dimensional wavelet coefficients is shown in Fig. 4.5 [32].

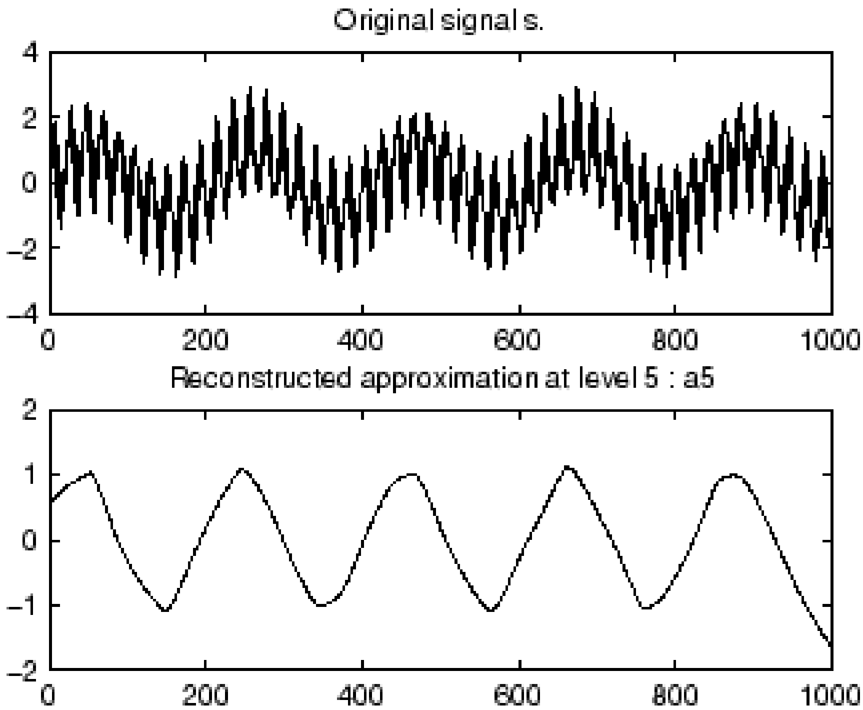


Figure 4.5: Reconstructing single branch from one dimensional wavelet coefficients.

In our thesis the wrcoef is used for the band extraction purpose. All the bands - gamma, beta, alpha, theta, delta bands can be extracted from the original EEG signal using this function. With the intention of only extracting the alpha band from the EEG signal we used a value of N = 4. The line of code in MATLAB given in Eq 4.4 which will eventually isolate the alpha frequency band from the rest and saved in a variable $D4$.

$$D4 = wrcoef('d', C, L, waveletFunction, 4); \%Alpha \tag{4.4}$$

### 4.3.3 Cognitive Load Index

Cognitive load index has been used in our thesis for the purpose of labeling ERD-ERS. According to Cognitive Load theory, It relates the following two topics: working memory restraints to the effectiveness of instruction.Learning process is executed in the working memory which has limited capacity and duration as it can hold $7 \pm 2$ chunks of information of a given time. A participant's cognitive load can be estimated by the parameters ERD-ERS. It has been mentioned by Parvez et al. that the alpha band power is increased during event-related synchronization (ERS) and decreased during event-related desynchronization (ERD) [27]. ERS or ERD is calculated by the Eq. 4.5.

$$\gamma = ((\rho_b - \rho_t)/\rho_b) * 100 \tag{4.5}$$

The MATLAB implementation of Eq. 4.5 is given in Eq 4.6.

$$ErdErs1 = (mean(restingPower) - originalPower)/mean(restingPower) * 100 \tag{4.6}$$

Thus on receiving the ERD-ERS value we can easily assess the cognitive load on the participants.

## 4.4 Classification

### 4.4.1 Five fold Cross Validation

Support vector machine (SVM) has been used to classify our data. It can easily define the data into hyperplane or a set of hyperplanes in a an infinite-dimensional space. This is a an easy procedure for classifying data which are non-stationary such as EEG data. All the trials which took place in the dataset are firstly divided into subsets and in our case it is $N = 5$. One of the subsets is chosen arbitrarily and set for testing and the other $N - 1$ subsets are used for training. In order to generate an optimal model of SVM, five-fold crossvalidation method is used.

Since $N - 1$ (80% of the subset) subsets are used for training and building the SVM model and the remaining randomly selected $N - 4$ subset (20% of the subset) to fit the model. If the model gets well fitted, we can say that the model is trained and the other 20% subset is used for testing. Fig. 4.6 shows the process of five fold cross validation. This testing is performed N-times and it's average is calculated with the help of three different metrics which are - specificity, accuracy and sensitivity [27] [31].

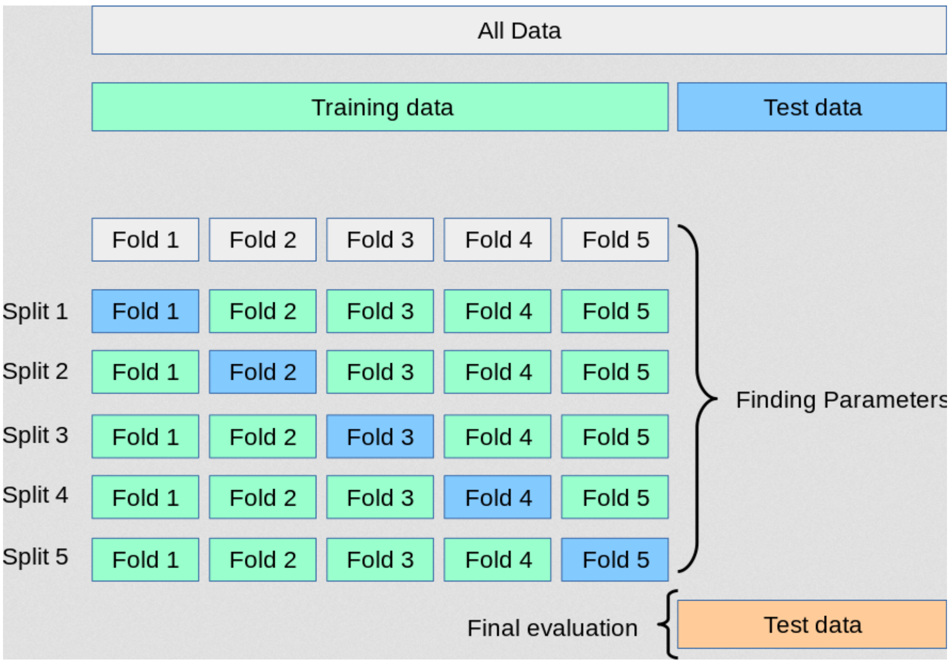


Figure 4.6: Five Fold Cross-Validation.

# Chapter 5

# Results and Discussion

## 5.1 Results

In this chapter the results from the classification of data will be given. Three basic metrics are used for classifying/ establishing whether the test data is well fitted or not. The metrics are specificity - also known as the true negative frequency (TNR), is the percentage of tests that test negative using the experiment in question [29], sensitivity - the proportion of positive factors that the classifier correctly identifies as positive [35] and accuracy - which is essentially the level of accurate labeling, either for an independent test set or with some variant of the principle of cross-validation [22]. The classification results are summarized in the Table 5.1.

For giving a visual representation of our classification we have used ROC (Reciever Operating Characteristic) curve. The ROC curve plots the specificity (true positive rate) in the x-axis and sensitivity(true negative rate) on the y-axis. The area under the ROC curve gives us the accuracy of the classification.

| Anodal | |
|---|---|
| Sensitivity | 86.44% |
| Specificity | 100% |
| Accuracy | 86.67% |
| Cathodal | |
| Sensitivity | 91.07% |
| Specificity | 75.00% |
| Accuracy | 88.33% |

Table 5.1: Classification results of anodal vs. Sham and cathodal vs. sham

### 5.1.1 Anodal

When applying anodal tDCS we get sensitivity of 86.44%, specificity of 100%, accuracy 86.67%. Five fold cross-validation has been used for classifying the data.a The ROC (Receiver Operating Characteristic) curve for anodal vs. sham stimulation has been given in Fig. 5.1.

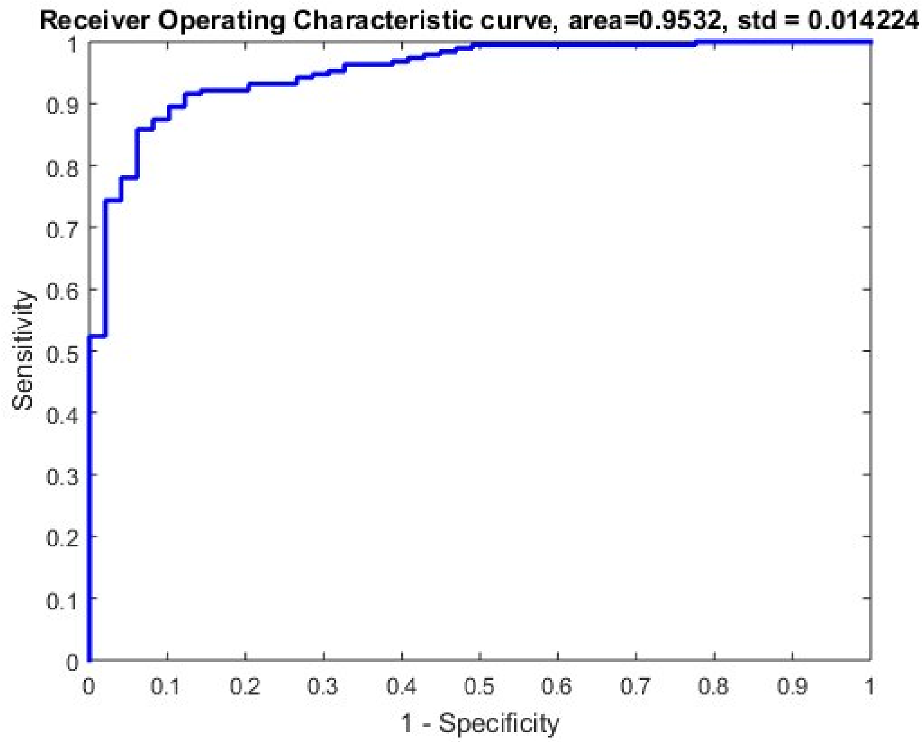


Figure 5.1: ROC curve for anodal vs sham during tDCS stimulation.

### 5.1.2 Cathodal

When we applied cathodal tDCS we get Sensitivity of 91.07%, Specificity of 75%, and accuracy of 88.33%. The ROC (Receiver Operating Characteristic) curve for cathodal vs. sham stimulation has been given in Fig. 5.2.

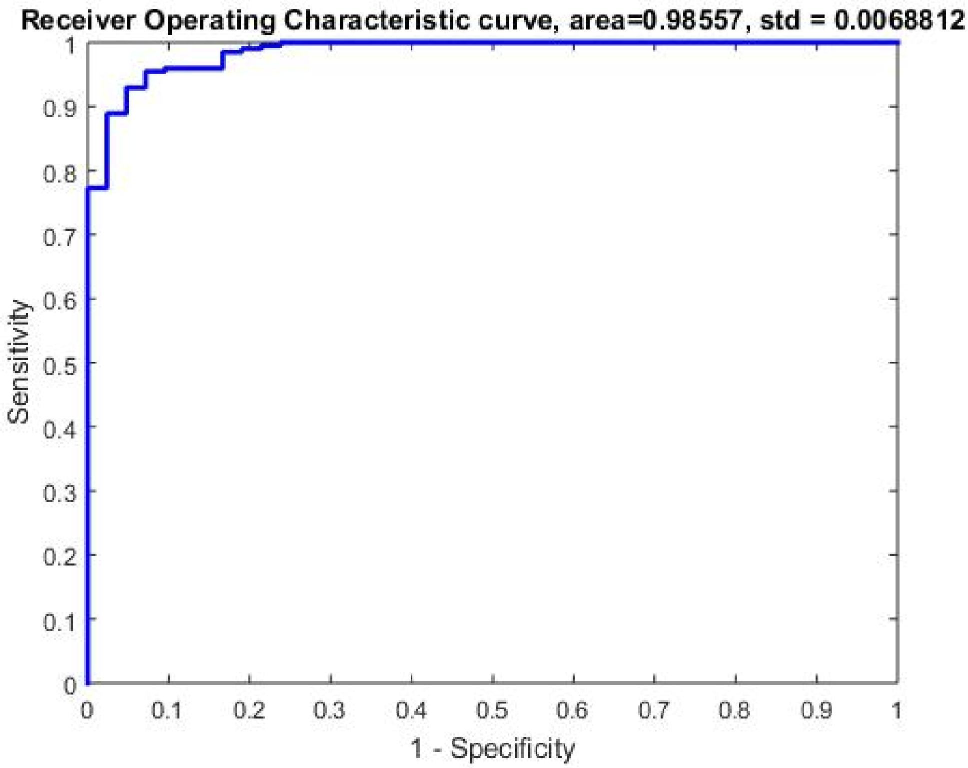


Figure 5.2: ROC curve for cathodal vs sham during tDCS stimulation.

## 5.2 Discussion

From the results we can see that for anodal stimulation we had an accuracy of 86.67% and for cathodal stimulation it is 88.33%. The results are quite satisfactory considering the processes used for band extraction, labelling and feature extraction. Further research needs to be done on this data-set while applying new methods for band extraction, labelling and feature extraction which could lead to better accuracy results. The accuracy results show that our training subset is quite well fitted with the test subsets. This shows that applying tDCS on the left hemisphere (dominant hemisphere) of the brain can actually cause ERD on the right side of the brain. This just shows that tDCS and neurofeedback has the potential to change the brainwaves of an individual. If proper tDCS and neurofeedback can be given to individuals in a controlled environment, it will have significant effects on that individual and may even change brain chemistry permanently. It can be a great start to rehabilitating patients with PTSD, addiction to substances, brain diseases like Alzheimer's disease, Parkinson's disease and even if the motor cortex is damaged due to stroke [15].

# Chapter 6

# Conclusion

From collecting the EEG signal to classifying the data using Cognitive load we can finally say that applying tDCS on the left hemisphere of the brain (dominant hemisphere) has significant effects on the brain frequencies. We have observed ERD on the right hemisphere of the brain after applying tDCS on the left side of the brain. It has a huge significance in the field of bioinformatics as this information can be used to treat brain abnormalities and diseases related to the brain. Some very common brain diseases such as Alzheimer's disease, Parkinson's disease, Dementia, Huntington's disease. Further research is needed to understand the inner workings of the brain and how tDCS affects the brain so that we can learn how to use this in helping brain disease patients. This research may also open doors for controlling robotic arms or other peripheral devices with the brain. Up until now we have a classification accuracy of 86.67% for anodal stimulation and 88.33% for cathodal stimulation to the left side and pre-frontal cortex of the brain chromatically. With the use of other feature extraction methods we may get results consisting of better accuracy, which will be an addition to this current research.

## 6.1 Limitations

Before and during the research work we have faced some problems which limited our research otherwise more extended and in depth research could have been possible. The first limitation that we faced was the unavailability of EEG capturing machines. This is why we needed to look for data-set online. The second limitation was the unavailability of tDCS applying machine as well as the participants for our research. The data-set that we have gathered included the presence of neurofeedback which induces familiarization but on the other hand we are observing ERD which wasn't stable over time. Removing the feedback wasn't possible in our case as we had only the dataset to work with but if neurofeedback wasn't applied we would have gotten a quite different result. Another point to be mentioned is that, the data-set includes participants who were healthy, we cannnot generalize these research over patient participants as the tDCS and neurofeedback may have different effects on their ERD. Finally, before we even started to do the research we had little to none previous knowledge about the topic at hand. We had to go through some literature review and did some background study in order to understand some of the present methodologies that is currently being used. These were some of the limitations that we had before and during the research work.

## 6.2 Future work

Our future work will include implementing other algorithms/ functions rather than $fft$ and *wpdec* for feature extraction. We can also use other band extracting functions other than *wavedec* and classify the data using other classification methods such as Classification Trees (CART), Partial Least Square Discriminant Analysis (PLSDA), K-Nearest Neighbors (kNN) etc. in order to see if the accuracy, specificity, sensitivity percentages changes. We will also try our best to get our own tDCS applying machine and EEG signal receiver machine in order to continue our research at our own pace and gathering data according to our needs. Since we have already showed that applying tDCS to the left side of the brain induces ERD on the right side of the brain, we would like to further our research about whether applying tDCS on the brain can help improve brain diseases like Alzheimer's disease, Parkinson's disease, Huntington's disease, Epilepsy.

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