

Processing of EEG for Detection of Saccade and Fix by Eliminating Blink

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CERTIFICATE OF APPROVAL *

The foregoing thesis is hereby approved as a credible study of engineering subject to warrant its acceptance as a prerequisite to obtain the degree for which it has been submitted. It is understood by this approval the undersigned do not endorse or approve any statement made, opinion expressed or conclusion drawn therein , but approve the thesis only for the purpose for which it is submitted.

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF
ACADEMIC THESIS

I hereby declare that this thesis titled “**Processing of EEG for Detection of Saccade and Fix by Eliminating Blink**” contains literature survey and original research work by the undersigned candidate, as part of his Degree of Master of Technology in Intelligent Automation and Robotics.

All information have been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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Abstract

Electroencephalography (EEG) is an emerging field of research. It is used to analyse brain activities by probing different areas of the scalp. The electronic signature of the brain is observed to be fairly similar when a subject performs similar task but differs in the level of the activity.

We believe that EEG signals if processed using the right methodology, will help in determining the cognitive behavior of a subject. One aspect of the cognitive behavior is intelligence. As mentioned earlier, the EEG signals are the signature of the brain activity of different regions of the subject. In this thesis we try to find ways to measure and determine the intelligence of a subject by making him/her to perform certain tasks. Based on the recorded EEG and EOG data we make an assessment of the subject's intelligence based of the proposed metrics.

EEG and EOG data are recorded at Axxonet India Pvt. Ltd. Placement of 32 electrodes were based on the standard 10-20 convention. Two electrodes were placed in the ocular region as per convention and the recording was performed using a notch filter of the range 0-75 Hertz. The tasks performed were very basic in nature eg. identifying the target object in a scene/map, reading a passage and find the number of times a given word is repeated. Raw EEG/EOG data collected were first preprocessed using different methods mentioned ahead and then the signal thresholding techniques were used to detect the blinks saccadic movements and fixes. Classification of a target/non target object was determined based on the presence of P300 signal in the corresponding probe. The saccadic movement, fixes and the blinks

determined the focus and way in which the subject scanned through the scene/map. Combined with the classification of P300 signal one can measure a subjects' scene/map reading intelligence.

In the recent development EEG has proven repeatedly to bring out new insights related to the activity of the brain in a noninvasive way. It is used in many fields in order to measure the effect of any activity that the subject performs or any stimuli that is given to the subject. With the help of Artificial Intelligence, analysis of EEG has reached a new level as it allows us to perform intractable operations which were otherwise not possible using classical techniques. In the marketing it has given a deeper insight to how consumers react to certain products. In the medical field prior prediction of seizure in epileptic patients is progressing every year. In the military application, where our thesis is focused on, EEG is used to measure the responsiveness of the candidate under examinations. The most popular area of application of EEG is Brain Controlled interface (BCI) where devices are being controlled with the help of the brain signals.

In the thesis we have extracted the Blink, Saccade and Fix artefacts from the EEG signal obtained from different subjects. The EEG signal were recorded while the subject was directed to analyse certain spatial scenes.

The processing of the EEG artefacts to understand the scene/ map reading capability of the subject were analyzed.

Table of Contents

Abstract.....	1
Chapter 1 : INTRODUCTION.....	9
1.1 Generalized Definition of Electroencephalography	9
1.2 EEG classification based on frequencies.....	10
1.2.1 Delta Waves.....	10
1.2.2 Theta Waves.....	11
1.2.3 Alpha Waves.....	11
1.2.4 Beta Waves.....	12
1.2.5 Gamma Waves	13
1.3 Applications of EEG	14
1.3.1 Medical Applications:	14
1.3.2 Commercial Applications:.....	14
1.3.3 Brain Computer Interface (BCI):.....	14
1.4 Generalized Definition of Electrooculography.....	15
1.5 Applications of EOG.....	15
1.7 Organisation of the Thesis.....	16
1.6 Summary.....	18
Chapter 2: Characteristics of EEG signal	20
2.1 Introduction.....	20
2.2 Blink Artefact	20
2.3 Saccade	21
2.3 Fixation.....	22
2.4 Summary	23
Chapter 3: Review of Research Literature on EEG	25
3.1 Introduction.....	25
3.2 Review of Methodology for processing of EEG Signals	26
3.2.1 Band Pass Filtering	26
3.2.2 Notch Filter.....	27
3.2.3 Continuous Wavelet Transform (CWT).....	28
3.2.4 Baseline Drift Removal.....	32
3.2.5 Wavelet Denoising	32
3.2.6 Median Filtering	33

3.2.7 Moving Average	34
3.3 Feature Extraction	36
3.3.1 Principal Component Analysis (PCA)	36
3.3.2 Independent Component Analysis (ICA)	36
3.4 Classification Techniques	37
3.4.1 Support Vector Machines (SVM)	37
3.4.2 K-Nearest Neighbour (KNN).....	38
3.4.3 Artificial Neural Network (ANN)	40
3.5 Review of applications using EEG	41
3.5.1 Medical Applications	41
3.5.2 Commercial Applications.....	42
3.5.3 Military Applications	42
3.5.4 Brain Computer Interface (BCI)	43
3.5.5 Internet of things(IOT)	45
3.5.6 Security	45
3.6 Summary	45
Chapter 4: Software and Hardware Required for capturing and analyzing EEG	48
4.1 Introduction.....	48
4.2 EEG acquisition: Axxonet's Brain Electro Scan System (BESS)	48
4.3 Analyzing EEG: <i>Softwares Required</i>	51
4.3.1 Matlab 2014a.....	51
4.4 EEGLAB TOOLBOX.....	57
4.4.1 EEGLAB Features.....	58
4.4.2 EEGLAB System Requirements.....	59
4.5 EDF Browser	61
4.5.1 EDF Browser features	61
4.6 Python	63
4.6.2 Python Features.....	64
4.6.3 Relevant libraries in python	66
4.7 Summary	68
Chapter 5: Data Acquisition.....	70
5.1 Introduction.....	70
5.2 BASIC PROTOCOL: Preparation of Human Subjects for EEG Studies	71

5.3 Subjects Data Selection.....	72
5.4 EEG acquisition setup block.....	72
5.5 Experimental Procedure.....	73
5.6 EOG Data Acquisition.....	74
5.7 Summary.....	77
Chapter 6: A Method to Detect Blink from the EEG Signal.....	79
6.1 Introduction.....	79
6.2 Process of EEG Data Acquisition.....	80
6.3 EOG Data Acquisition.....	80
6.4 Blink Detection.....	82
6.5 Results.....	87
6.6 Applications.....	88
6.7 Summary.....	88
Chapter 7: Saccade & Fix Detection from EOG signal.....	91
7.1 Introduction.....	91
7.2 Methods.....	92
7.2.1 Block Diagram.....	92
7.2.2 Baseline Drift Removal.....	92
7.2.3 Noise Removal.....	93
7.2.4 Median Filtering.....	93
7.2.5 Wavelet Denoising.....	94
7.2.6 Saccade Detection.....	95
7.2.7 Fixation.....	95
7.3 Summary.....	97
Chapter 8: Conclusion & Future Scope of Work.....	99
8.1 Conclusion.....	99
8.2 Future Scope of Work.....	100
8.2.1 P300 Analysis.....	100
8.2.2 Saccade Fix Graph.....	101
8.2.3 Eye Gaze direction prediction.....	102
8.2.4 Blink Application.....	104
Appendix.....	105

List of figures

Fig 1. 1 (a) 10-20 electrode placement for 32 channel EEG acquisition system (b) Plot for EEG data from FP1, FP2, A1, A2 channel.....	9
Fig 1. 2 (a) EOG electrode placement for recording, (b) Sample of recorded EEG signal	16
Fig 2. 1 Blinks observed in A1 and A2 electrode.....	21
Fig 2. 2 Plot of a fixation in between two saccades.....	23
Fig 3. 1 Frequency characteristics of Band pass filter.....	27
Fig 3. 2 Notch filter frequency response.....	28
Fig 3. 3 Different wavelets used for wavelet transform	29
Fig 3. 4 Wavelet Decomposition at level 3	30
Fig 3. 5 Baseline Drift	32
Fig 3. 6 Comparison between median filtered signal and the original signal.....	34
Fig 3. 7 Simple Moving Average vs Exponential Moving Average vs Original Signal.....	35
Fig 3. 8 Illustration of trained hyperplane	38
Fig 3. 9 KNN applied with $k = 9$	39
Fig 3. 10 (a) Operation of 1 neural unit of the neural network. Here f is predefined function known as an activation function.(b) 3-layer neural network	40
Fig 3. 11 A test system for assessing workload and engagement of computer gamers.	43
Fig 3. 12 Flow chart for mind controlled Wheelchair	44
Fig 3. 13 Mind controlled Gaming device	44
Fig 4. 1 EEG acquisition in real time using BESS.....	50
Fig 4. 2 EEGLAB GUI window in Matlab	59
Fig 4. 3 Visualizing a recording session with EDF Browser	61
Fig 4. 4 Python Shell Terminal.....	64
Fig 5. 1 EEG Acquisition setup.....	72
Fig 5. 2 Cross sectional view of 10-20 electrode placement diagram.	75
Fig 5. 3 Subject wearing EEG cap while recording of EEG and EOG signal	75
Fig 5. 4 Slide to count the number of planes	76
Fig 5. 5 Passage shown to the subject	77

Fig 6. 1 Cross sectional view of 10-20 electrode placement diagram.	81
Fig 6. 2 Subject wearing EEG cap while recording of EEG and EOG signal	81
Fig 6. 3 EOG electrode placement on subject.....	82
Fig 6. 4 32 Channel EEG data plot using EEGLAB Toolbox (Version 14.1.2b)	83
Fig 6. 5 Two blink samples and the resulting signal after applying Moving Average technique..	84
Fig 6. 6 Overlapped Plot of 29 blink samples.....	84
Fig 6. 7 Detection of blinks in EEG data stream	86
Fig 7. 1 Comparison of the original signal and baseline removed signal.....	93
Fig 7. 2 Illustration of filtering techniques applied on the signal	94
Fig 7. 3 CWT coefficients of the signal with a threshold ± 25 (top) and Corresponding Saccades (bottom)	96
Fig 7. 4 Demonstration of fix and saccades	97
Fig 8. 1 Electrode placement for EOG recording	102
Fig 8. 2 Eye gaze directions	103

List of Tables

Table 1. 1 EEG classification according to frequency	13
Table 3. 1 Block Diagram for EEG signal processing techniques	26
Table 3. 2 Block Diagram for EEG applications	41
Table 6. 1 Algorithm accuracy for 2 subjects' EEG data	87
Table 7. 1 Block Diagram for Saccade Detection System	92
Table 8. 1 Eye-Movement direction table with electrode encoder	103

Chapter 1: *INTRODUCTION*

1.1 Generalized Definition of Electroencephalography

The brain consists of trillions of cells, half of which are neurons and the other half of which help and facilitate the activity of neurons. These neurons are densely interconnected via synapses, which act as gateways of inhibitory or excitatory activity [1].

Any synaptic activity generates a subtle electrical impulse referred to as a postsynaptic potential. It is difficult to reliably detect the burst of a single neuron without direct contact with it. However, whenever thousands of neurons fire in sync, they generate an electrical field which is strong enough to spread through tissue, bone, and skull. Eventually, it can be measured on the head surface.

Electroencephalography, or EEG, is the physiological method of choice to record the electrical activity generated by the brain via electrodes placed on the scalp surface. For faster application, electrodes are mounted in elastic caps similar to bathing caps, ensuring that the data can be collected from identical scalp positions across all respondents.

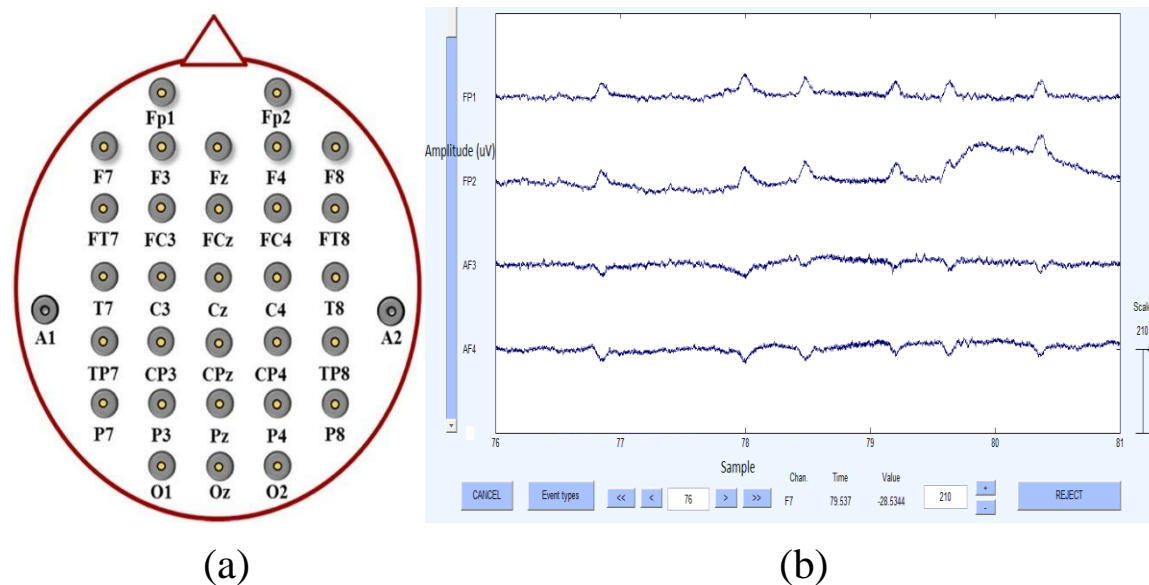


Fig 1. 1 (a) 10-20 electrode placement for 32 channel EEG acquisition system (b) Plot for EEG data from FP1, FP2, A1, A2 channel

Fig.1.1 describes placement of electrodes on scalp for EEG recording (a). 10-20 electrode placement is used for the experiments. Hence, 4 channel EEG data is plotted (b).

Yet another way of defining EEG is that EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. Clinically, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp [12].

1.2 EEG classification based on frequencies

The EEG signal generally varies from 1-50 hz and 10-100 μ V when measured from skull surface. In order of lowest frequency to higher, the five brain waves are: Delta, Theta, Alpha, Beta and Gamma.

1.2.1 Delta Waves

Delta waves are associated with deep levels of relaxation and restorative sleep, to remember this simply think of 'Delta' for 'Deep'. They are the slowest recorded brain waves in humans and higher levels are more commonly found in young children. During the aging process, lower Delta waves are produced. Research tells us that Delta waves are attributed to many of our unconscious bodily functions such as regulating the cardiovascular and the digestive systems. Healthy levels of Delta waves can contribute to a more restful sleep, allowing us to wake up refreshed, however irregular delta wave activity has been linked to learning difficulties or issues maintaining awareness.

Frequency range: 0 Hz to 4 Hz

High levels: Brain injuries, learning problems, inability to think

Low levels: Inability to rejuvenate body, inability to revitalize the brain, poor sleep

Optimal range: Healthy immune system, restorative REM sleep

1.2.2 Theta Waves

Theta waves known as the ‘suggestible waves’, because of their prevalence when one is in a trance or hypnotic state. In this state, a brain’s Theta waves are optimal and the patient is more susceptible to hypnosis and associated therapy. The reasoning for this is that Theta waves are commonly found when you daydream or are asleep, thus exhibiting a more relaxed, open mind state. Theta waves are also linked to us experiencing and feeling deep and raw emotions, therefore too much theta activity may make people prone to bouts of depression. Theta does however have its benefits of helping improve our creativity, wholeness and intuition, making us feel more natural. It is also involved in restorative sleep and as long as theta isn’t produced in excess during our waking hours, it is a very helpful brainwave range.

Frequency range: 4 Hz to 8 Hz

High levels: ADHD or hyperactivity, depressive states, impulsive activity or inattentiveness

Low levels: Anxiety symptoms, poor emotional awareness, higher stress levels

Optimal range: Maximum creativity, deep emotional connection with oneself and others, greater intuition, relaxation

1.2.3 Alpha Waves

Alpha waves are the ‘frequency bridge’ between our conscious thinking (Beta) and subconscious (Theta) mind. They are known to help calm you down and promote feelings of deeper relaxation and content. Beta waves play an active role in network coordination and communication and do not occur until three years of age in humans. In a state of stress, a phenomenon called ‘Alpha blocking’ can occur which involves excessive Beta activity and little Alpha activity. In this scenario, the Beta waves restrict the production of alpha because our body is reacting

positively to the increased Beta activity, usually in a state of heightened cognitive arousal.

Frequency range: 8 Hz to 12 Hz

High levels: Too much daydreaming, over-relaxed state or an inability to focus

Low levels: OCD, anxiety symptoms, higher stress levels

Optimal range: Ideal relaxation

1.2.4 Beta Waves

Beta waves are the high frequency waves most commonly found in awake humans. They are channelled during conscious states such as cognitive reasoning, calculation, reading, speaking or thinking. Higher levels of Beta waves are found to channel a stimulating, arousing effect, which explains how the brain will limit the amount of Alpha waves if heightened Beta activity occurs. However, if you experience too much Beta activity, this may lead to stress and anxiety. This leads you feeling overwhelmed and stressed during strenuous periods of work or school. Beta waves increased by drinking common stimulants such as caffeine or L-Theanine, or by consuming Nootropics or cognitive enhancers such as Lucid. Think of Beta as the stressed state of mind.

Frequency range: 12 Hz to 40 Hz

High levels: Anxiety, inability to feel relaxed, high adrenaline levels, stress

Low levels: Depression, poor cognitive ability, lack of attention

Optimal range: Consistent focus, strong memory recall, high problem solving ability.

1.2.5 Gamma Waves

Gamma waves are a more recent discovery in the field of neuroscience, thus the understanding of how they function is constantly evolving. To date, it's known that Gamma waves are involved in processing more complex tasks in addition to healthy cognitive function. Gamma waves are found to be important for learning, memory and processing and they are used as a binding tool for our senses to process new information. In people with mental disabilities, much lower levels of Gamma activity is recorded. More recently, people have found a strong link between meditation and Gamma waves, a link attributed to the heightened state of being or 'completeness' experienced when in a meditative state.

Frequency range: Above 40 Hz

High levels: Anxiety, stress

Low levels: Depression, ADHD, learning issues

Optimal range: Information processing, cognition, learning, binding of senses.

For ease of reading the EEG classification can be tabulated as below-

Sl. No	Type	Frequency (Hz)	State of Mind
1	Delta	0-4	Healthy immune system, restorative REM sleep
2	Theta	4-8	Maximum creativity, deep emotional connection with oneself and others, greater intuition, relaxation
3	Alpha	8-12	Ideal relaxation
4	Beta	12-40	Consistent focus, strong memory recall, high problem solving ability
5	Gamma	Above 40	Information processing, cognition, learning, binding of senses

Table 1. 1 EEG classification according to frequency

1.3 Applications of EEG

EEG has given way to many area of new research and application besides its traditional application in medicine. Some emerging applications are in the field of BCI, Neuromarketing, Cognitive capacity building and therapy etc. Some of the key applications of EEG are as described below-

1.3.1 Medical Applications:

- The EEG is used to evaluate several types of brain disorders. When epilepsy is present, seizure activity will appear as rapid spiking waves on the EEG.
- People with lesions of their brain, which can result from tumours or stroke, may have unusually slow EEG waves, depending on the size and the location of the lesion.
- The test can also be used to diagnose other disorders that influence brain activity, such as Alzheimer's disease, certain psychoses, and a sleep disorder called narcolepsy [2].

1.3.2 Commercial Applications:

- In the field of neuromarketing, economists use EEG research to detect brain processes that drive consumer decisions, brain areas that are active when we purchase a product/service, and mental states that the respective person is in when exploring physical or virtual stores. [3,4]

1.3.3 Brain Computer Interface (BCI):

- Analyse EEG signals of paralyzed patients and provide them a degree of independence for certain tasks like, Home based application Control [5], Wheelchair Control [6] etc.
- EEG based assistive mobile robots [7, 8].
- Measure a person's cognitive ability and improvement in cognitive functions [9,10].

1.4 Generalized Definition of Electrooculography

Electrooculography, or EOG, is used to record eye movements during electronystagmographic testing. It is based on the corneo-retinal potential (difference in electrical charge between the cornea and the retina), with the long axis of the eye acting as a dipole. This potential is thought to result from the metabolic activity of the retina. When the eye rotates in the orbit, the dipole also rotates. Silver–silver chloride electrodes placed near the orbit can be used to record this electrical difference. To measure eye movement, pairs of electrodes are typically placed either above and below the eye or to the left and right of the eye. If the eye moves from center position toward one of the two electrodes, this electrode "sees" the positive side of the retina and the opposite electrode "sees" the negative side of the retina. Consequently, a potential difference occurs between the electrodes. Assuming that the resting potential is constant, the recorded potential is a measure of the eye's position.

In other words, a record of the standing voltage between the front and back of the eye that is correlated with eyeball movement (as in REM sleep) and obtained by electrodes suitably placed on the skin near the eye (Figure 1.2 a) is called EOG.

1.5 Applications of EOG

Electrooculography was used by Robert Zemeckis and Jerome Chen, the visual effects supervisor in the movie *Beowulf*, to enhance the performance capture by correctly animating the eye movements of the actors. The result was an improvement over the technique used for the film *The Polar Express*. Some of the key applications of EOG are as follows-

- EOG can be used to detect eye movement and related artefacts. Blink, saccade and fix are three major artefacts that can be analyzed from EOG.
- Blink artefacts are considered as noise to the signal, therefore filtering those results in more accurate experimental information to

analyze further [11]. Blink detection can also be used for drowsiness detection, attention analysis etc.

→ Saccades are voltage deflection when eye moves randomly from one fix to another.

The deflection observed in the plot (Figure 1.2 b) corresponds to saccades of various kinds which is explained in later chapters.

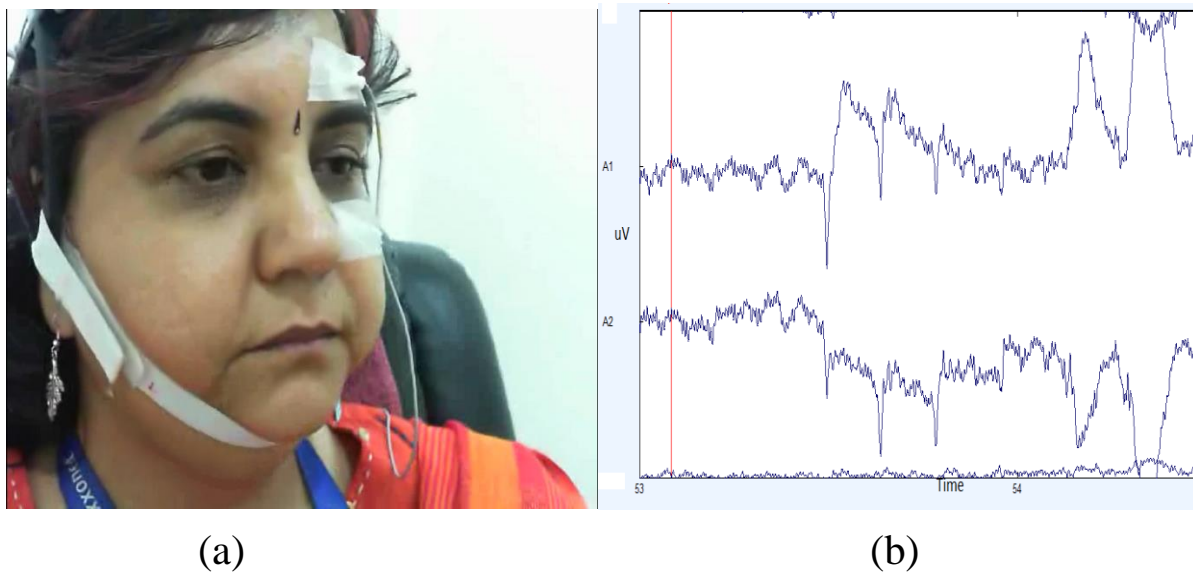


Fig 1. 2 (a) EOG electrode placement for recording, (b) Sample of recorded EEG signal

1.7 Organization of the Thesis

This thesis is organized into eight (8) chapters. Each chapter deals with different artefacts and characteristics of EEG and the experiments conducted in the project.

Chapter 1 gives an introduction about EEG. It starts with the generalized definitions of EEG. The classification of EEG signal into alpha, beta, gamma, delta, theta signal depending on its frequency range and voltage threshold is tabulated for ease of understanding of the first

time reader. After the physical interpretation of the waves in to the physical interpretation of the subject is described in this chapter.

Chapter 2 describes some of the most important characteristics of EEG signal, such as – Blink, Saccade and Fixation. Blink is associated with artefacts in the signal where saccade are observed as a result of ocular movement of the eye. Fixation describes the concentration of human observer at a particular object.

Chapter 3 gives an overview of the different preprocessing, processing and post-processing (classification) techniques available in literature. EEG signals are low in amplitude and high in frequency in characteristics. Therefore, in the process of amplification and quantization noise may get involved with the signal. The preprocessing is required for removing those unwanted noise signals for further analysis. Hence, the signal is processed for feature extraction and finally classified to obtain optimistic results.

Another part of this review comes in terms of applications. Beside its medicinal application, EEG is now getting implemented in the field of IOT, BCI, Military and many more.

Chapter 4 reveals hardware and software available for EEG signal recording and processing. There are 4-256 channel EEG acquisition system available according to the need of application. In the software counterpart Matlab along with different EEG toolbox, like – EEGLAB, Biosig, Brainwave etc. are still best suited for EEG data analysis. Python is also emerging for EEG processing due to its open source availability and libraries compatible of reading EEG files. EDF Browser is another excellent open source tool to visualize EEG signal.

Chapter 5 is a guideline for EEG data acquisition using 10-20 electrode placement with 32 channel EEG data recording system (BESS-32). EOG electrodes were also placed to get artefact of EEG.

The blink detection technique is depicted in **Chapter 6**. It gives the idea that normal thresholding could not be applied directly on the DC offset value as it is highly varying along the signal. Therefore, taking the gradient of the signal and applying a modified threshold to detect the blink is described in this chapter.

Saccade and fix detection is described as the content of **Chapter 7**. Along with Baseline Drift Removal, Wavelet Denoising is applied on noise removal techniques. Hence, CWT with ‘Haar’ wavelet is recorded as the best suited for saccade detection process. After successful detection the results are plotted and compared with video recorded during the session to compare the accuracy of the detection of saccades.

Chapter 8 portrays summary of the thesis and its future scope of work. The P300 analysis, SFG, Eye movement direction prediction and Blink applications are taken as the most important path for future research.

1.6 Summary

This chapter gives an overview of EEG and EOG signal and their applications. EEG signal can be next evolutionary research as BCI applications are growing exponentially in healthcare, IOT, Virtual Reality, Military application etc. It can also be used for driver / pilot assistance by performing drowsiness and consciousness detection. The main constrain with EEG signal is that it consists low strength and high frequency. A lot of pre-processing is required to achieve the signal which may include noise. In later chapters we discuss about this processes exclusively.

References:

1. <https://imotions.com/blog/what-is-eeeg/>
2. <https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/electroencephalogram-eeeg>
3. Vlăsceanu Sebastian, Neuromarketing and Evaluation of Cognitive and Emotional Responses of Consumers to Marketing Stimuli., *Procedia - Social and Behavioral Sciences*, Volume 127, 2014, Pages 753-757, ISSN 1877-0428, <https://doi.org/10.1016/j.sbspro.2014.03.349>.
4. Marcel Bastiaansen, Sebastiaan Straatman, Eric Driessen, Ondrej Mitás, Jeroen Stekelenburg, Lin Wang, My destination in your brain: A novel neuromarketing approach for evaluating the effectiveness of destination marketing, *Journal of Destination Marketing & Management*, Volume 7, 2018, Pages 76-88, ISSN 2212-571X, <https://doi.org/10.1016/j.jdmm.2016.09.003>.
5. RPIT SRIVASTAVA, MUKUND LAL, DARSH JAIN, MOHAMMAD FURKAN, ABHILASH SINGH, EEG BASED HOME APPLIANCE CONTROL FOR PROVIDING GUIDANCE TO PARALYZED PERSON, *International Journal of Electrical, Electronics and Data Communication*, ISSN: 2320-2084 Volume-3, Issue-1, Jan.-2015
6. A. Maksud, R. I. Chowdhury, T. T. Chowdhury, S. A. Fattah, C. Shahanaz and S. S. Chowdhury, "Low-cost EEG based electric wheelchair with advanced control features," *TENCON 2017 - 2017 IEEE Region 10 Conference, Penang, 2017*, pp. 2648-2653. doi: 10.1109/TENCON.2017.8228309
7. Chae, Yongwook & Jeong, Jaeseung & Jo, Sungho. (2012). Toward Brain-Actuated Humanoid Robots: Asynchronous Direct-Control Using an EEG-Based BCI. *IEEE Transactions on Robotics*. 28. 10.1109/TRO.2012.2201310.
8. N Murali Krishnan *et al* 2016 *IOP Conf. Ser.: Mater. Sci. Eng.* **121** 012017 DOI: <https://doi.org/10.1088/1757-899X/121/1/012017>
9. M. A. B. S. Akhanda, S. M. F. Islam and M. M. Rahman, "Detection of Cognitive State for Brain-Computer Interfaces," 2013 International Conference on Electrical Information and Communication Technology (EICT), Khulna, 2014, pp. 1-6. doi: 10.1109/EICT.2014.6777878
10. Mora Sanchez, Aldo & Gaume, Antoine & Dreyfus, Gérard & Vialatte, Francois. (2015). A cognitive brain-computer interface prototype for the continuous monitoring of visual working memory load. 10.1109/MLSP.2015.732437.
11. Kong, Xuan & F. Wilson, Glenn. (1998). A new EOG-based eyeblink detection algorithm. *Behavior research methods, instruments, & computers: a journal of the Psychonomic Society, Inc.* 30. 713-719. 10.3758/BF03209491.
12. Niedermeyer E.; da Silva F.L. (2004). *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*. Lippincott Williams & Wilkins. ISBN 978-0-7817-5126-1.

Chapter 2: *Characteristics of EEG signal*

2.1 Introduction

EOG signal contains eye movement related information. There are three types of behavior that can vividly observed in EOG signal. Such as - Blink, Saccade and Fix. Among them saccade and fix are considered for EEG signal analysis, where Blink is considered as artefacts [1] and more often eliminated for further processing of original signal. We proposed a method to detect blink, saccade and fix from EOG signal which is discussed in upcoming chapters.

2.2 Blink Artefact

Artefacts are elements that appear in an experimental result, but are not actually characteristic of the actual entity being studied. In physiological signal acquisition, they are introduced from extraneous sources such as electrical or mechanical interference, or incorrect experimental protocol on the part of experimenter or subject.

Eyelid closure, also referred as "blink", is the passive movement of the Levator Palpebrae Muscle (LPM), as its innervation ceases. Eyelid and eye movements are coordinated in order not to interfere with each other. During upwards gaze (when the eye looks/moves upwards) the eyelid does not cover the pupil, while during downwards gaze (when the eye looks/moves downwards) the eyelid protects the upper part of the eyeball.

In EOG signal, blinks are observed as a high fluctuation of voltage (peak) in continuous signal [2]. But the DC offset value is very high, therefore it cannot be segregated using normal thresholding. Figure 1 describe blinks as observed in EOG signal. Here two channel data is plotted where A1 electrode is placed above eyelid and A2 is placed below eyelid. The behavior is show in figure 2.1. The high deflections refer to blinks.

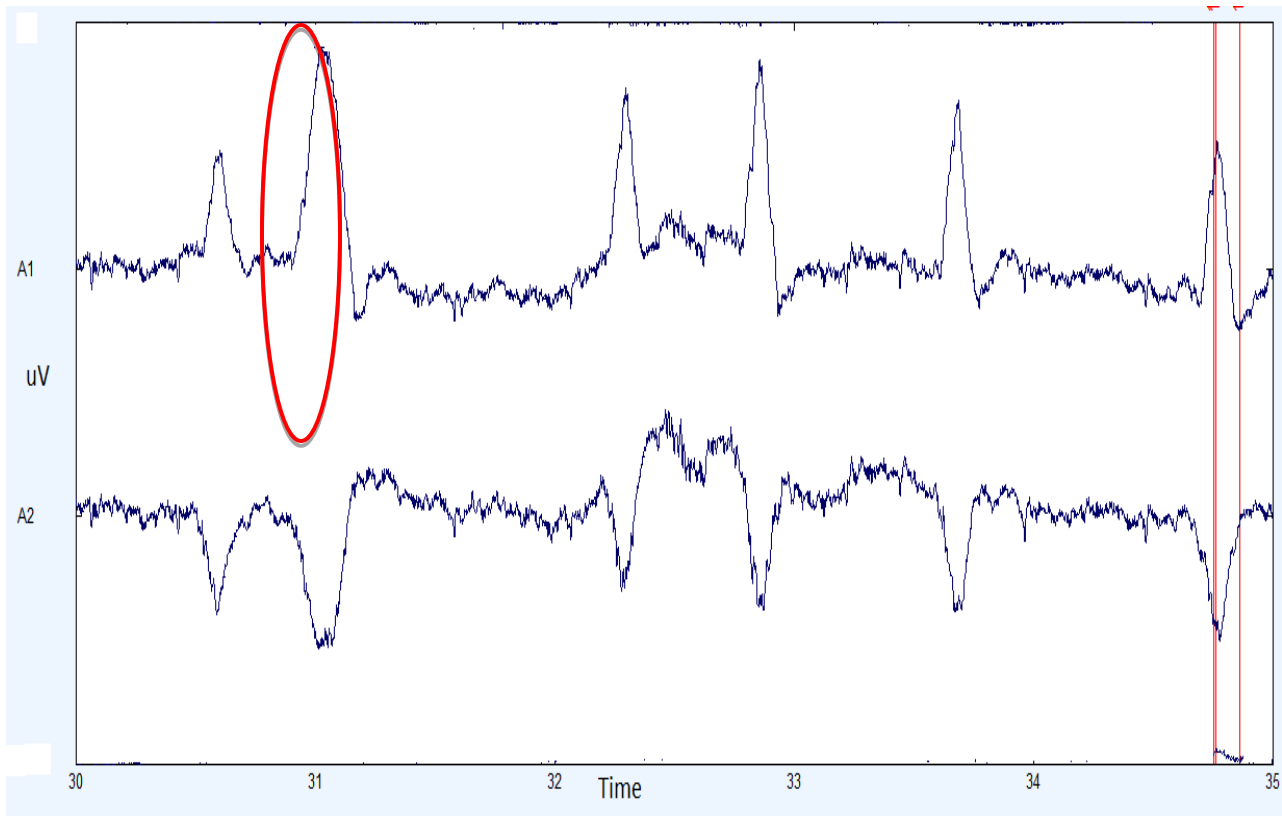


Fig 2. 1 Blinks observed in A1 and A2 electrode

2.3 Saccade

A saccade is a quick, simultaneous movement of both eyes between two or more phases of fixation. Those are rapid eye movements that allow us to quickly scan a visual scene. The eye focuses on a position for only a brief moment, before quickly jumping to the next. Saccades can be carried out voluntarily (try looking at one position and then adjusting your gaze to a position nearby – a saccade will carry out the transition), but they are largely done automatically. They are also carried out even if you are trying to hold your gaze at a single spot – a fixation is mostly just a series of saccades that are within a narrow area. At the end of some saccades, a small, oppositely directed saccade (a dynamic overshoot) occurred.

These small movements result in sudden high deflections in voltage as observed in EOG signals. Saccades can be classified as

Vertical, horizontal and micro saccades [8].Figure 2.1 shows two example of two saccades in between which a fix is present.

2.3 Fixation

Fixation or visual fixation is the maintaining of the visual gaze on a single location. The term "fixation" can either be used to refer to the point in time and space of focus or the act of fixating. Fixation, in the act of fixating, is the point between any two saccades, during which the eyes are relatively stationary and virtually all visual input occurs. In the absence of retinal jitter, a laboratory condition known as retinal stabilization, perceptions tend to rapidly fade away [3,4].

To maintain visibility, the nervous system carries out a mechanism called fixational eye movement, which continuously stimulates neurons in the early visual areas of the brain responding to transient stimuli. There are three categories of fixational eye movements: microsaccades, ocular drifts, and ocular microtremor. Although the existence of these movements has been known since the 1950s, only recently their functions have started to become clear [5,6]. In figure 2.2 the green circled area is named as a fixation. It occurs in between two corresponding saccades.

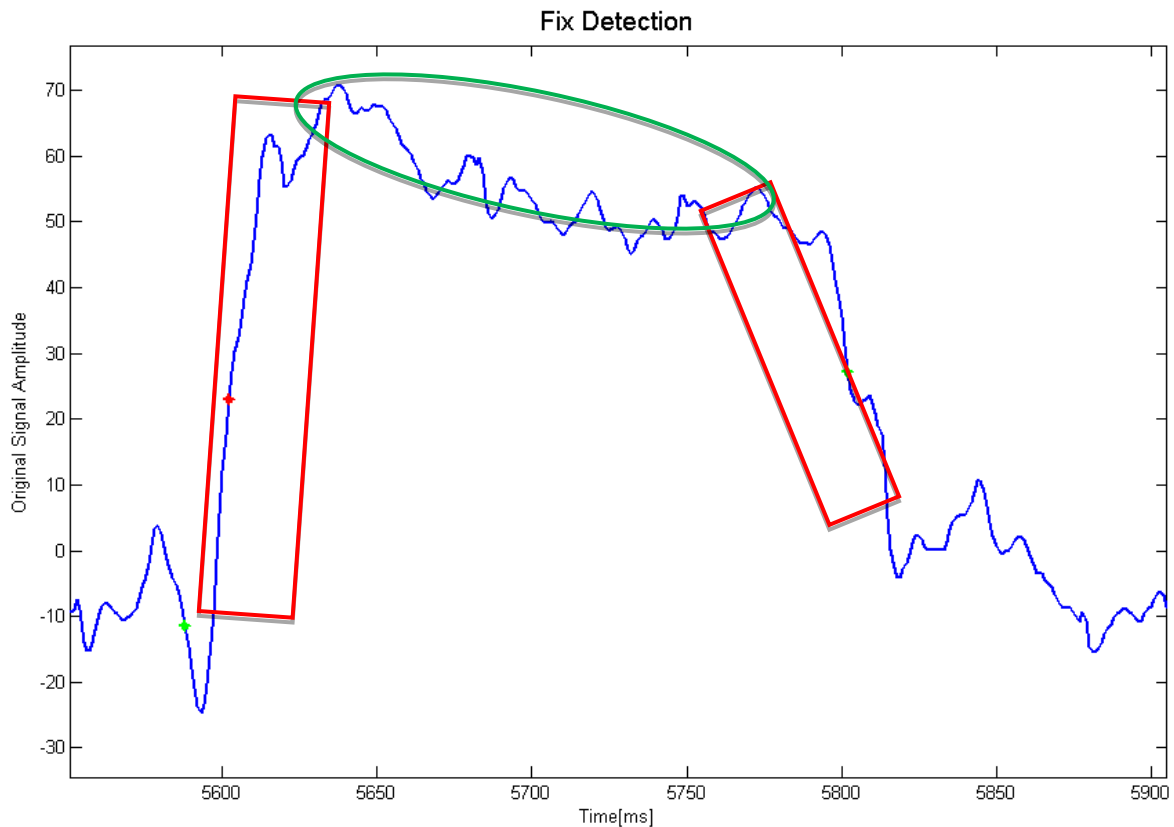


Fig 2. 2 Plot of a fixation in between two saccades

2.4 Summary

The results of a study indicate that blinks clearly affect the dynamic properties of accompanying saccades [7]. Therefore, we prefer to remove blinks first from the original signals. The process is describe in chapter 6. The method of saccade detection is described in chapter 7. This has many useful applications in various sectors as described in chapter 1. Studies of the dynamic properties of saccades need to carefully document the occurrence of blinks, which may substantially affect the results [7].

References

1. Hong Zeng and Aiguo Song, "Removal of EOG Artifacts from EEG Recordings Using Stationary Subspace Analysis," *The Scientific World Journal*, vol. 2014, Article ID 259121, 9 pages, 2014. <https://doi.org/10.1155/2014/259121>.
2. Gratton, G. *Behavior Research Methods, Instruments, & Computers*(1998)30: 44. <https://doi.org/10.3758/BF03209415>
3. Pritchard R.M., Heron W., & Hebb D.O. (1960). Visual Perception Approached by the Method of Stabilized Images. *Canadian J. Psych.*, 14, 67–77.
4. Coppola, D; Purves, D (1996). "[The Extraordinarily Rapid Disappearance of Entoptic Images](#)". *Proceedings of the National Academy of Sciences of the USA*. **93**: 8001–8004.
5. Collewijn, Han; Kowler, Eileen (2008-01-01). "[The significance of microsaccades for vision and oculomotor control](#)". *Journal of Vision*. **8** (14):20.1–21. [doi:10.1167/8.14.20](#). [ISSN 1534-7362](#). [PMC 3522523](#). [PMID 19146321](#)
6. Troncoso, Xoana G.; Macknik, Stephen L.; Martinez-Conde, Susana (2008-01-01). "Microsaccades counteract perceptual fillingin". *JournalofVision*. **8** (14):15.19. [doi:10.1167/8.14.15](#). [ISSN 1534-7362](#). [PMID 19146316](#).
7. Klaus G. Rottach, Vallabh E. Das, Walter Wohlgemuth, Ari Z. Zivotofsky, and R. John Leigh. "Properties of Horizontal Saccades Accompanied by Blinks". 01 JUN 1998 <https://doi.org/10.1152/jn.1998.79.6.2895>
8. <https://www.youtube.com/watch?v=P6uTlNyNaTs>

Chapter 3: *Review of Research Literature on EEG*

3.1 Introduction

EEG Signals are a measure of the electrical activity of the brain. The cortical nerve cell inhibitory and excitatory postsynaptic potentials generate the EEG signals. These postsynaptic potentials summate in the cortex and extend to the scalp surface where they are recorded as EEG. A typical EEG signal, measured from the scalp, will have an amplitude of about 10 μV to 100 μV and a frequency in the range of 1 Hz to about 100 Hz. While recording the signal, it encounters a number of interferences and/or artifacts get added. Eye Blinks, powerline interferences to name a few. Thus EEG signals become highly non-Gaussian, nonstationary and have a nonlinear nature [1]. The brain signals are highly complex and random in nature. Their characteristics strongly depend on the individual, age and mental state. The occurrence of symptoms is also at random in time scale. Hence, understanding the behavior and dynamics of billions of interconnected neurons involves several linear and nonlinear signal processing techniques and its correlation to the physiological events.

The preprocessing techniques if implemented correctly will help us give better information about the activity in the brain and also enable us to use it to control /detect/ remove certain points of interest eg. Blink artifact removal.

A block diagram including EEG signal processing is given below which depicts the sections of this review.

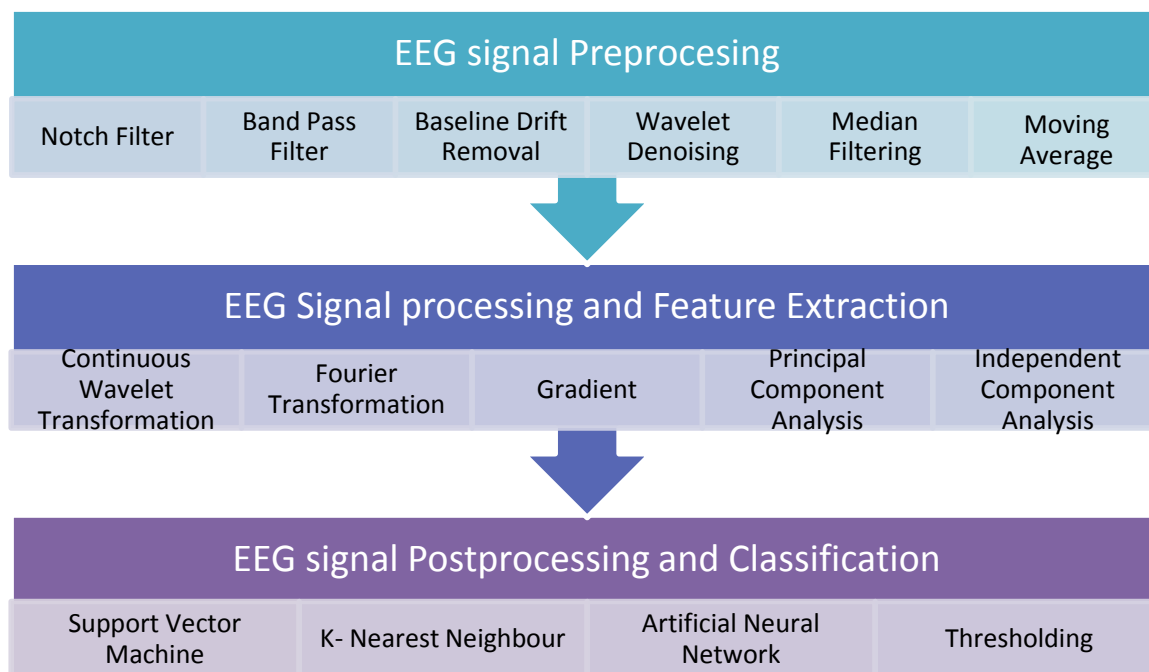


Table 3. 1 Block Diagram for EEG signal processing techniques

3.2 Review of Methodology for processing of EEG Signals

Processing of the EEG signal involves a careful analysis of it. Depending on the application or the type of information we want to extract, processing of the EEG signal differs accordingly. Below are a few of the processing techniques that are commonly used to extract useful information or remove the unwanted noise from it.

3.2.1 Band Pass Filtering

The most ideal filter design would be one that removes all of the electrical noise or artifact from the EEG and only allows true cerebral activity to pass through. Unfortunately, no such “smart” filters exists; filters can only remove waves according to rigid mathematical rules. Luckily, there are good rationales for filtering out certain components of EEG signals using fairly simple mathematical assumptions. These assumptions are based on the idea that the brain only generates EEG

waves within a certain range of frequencies and that any activity outside that range (unusually slow activity and unusually fast activity) is not likely to be of cerebral origin. Indeed, one of the general assumptions of EEG filter design is that activities well below 1 Hz and well above 35 Hz do not arise from the brain and likely represent electrical noise or artifact.

EEG filters are typically set up so that one filter rejects the majority of very high-frequency activity and another filter rejects the majority of very low-frequency activity. The range of frequencies between these unwanted high and low frequencies that is allowed to pass through the filter setup is referred to as the bandpass. Below figure 3.1 describes the frequency characteristics of the band pass filter.

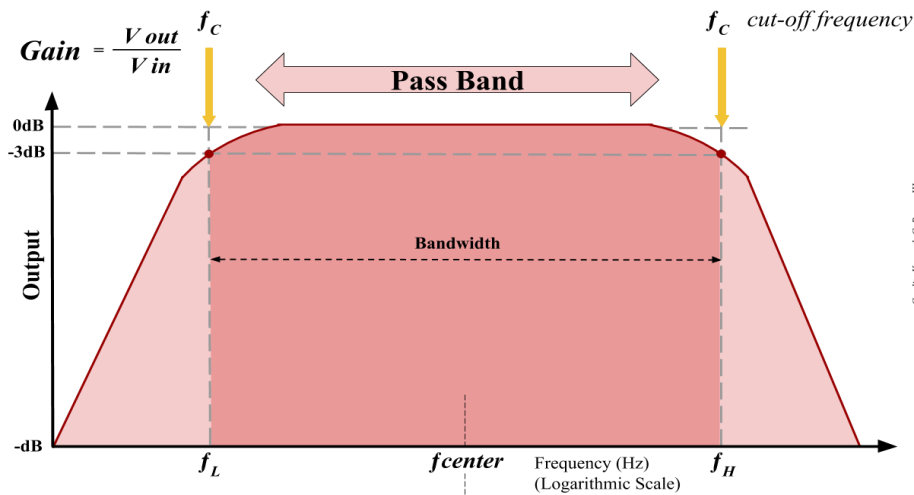


Fig 3. 1 Frequency characteristics of Band pass filter

3.2.2 Notch Filter

Notch filter are certain filters which can stop signals of certain frequency to be filtered out. After recording the raw eeg signal one of the most apparent noise that will be present in the signal in the power line signal frequency. notch filter at 60 Hz / 50 Hz is used to filter out power line

noise with minimal disruption to the rest of the signal. As explained in the figure 3.2 here f_c should be 60Hz.

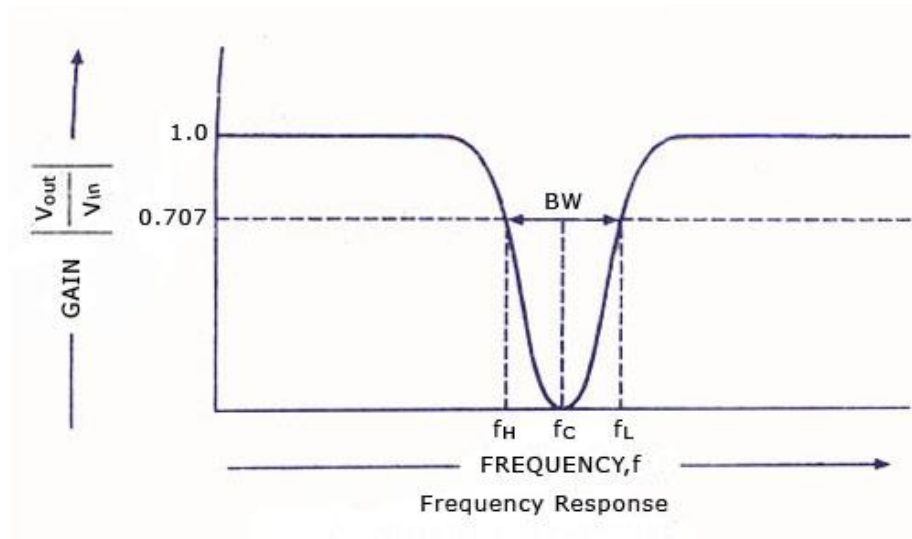


Fig 3. 2 Notch filter frequency response

3.2.3 Continuous Wavelet Transform (CWT)

A wavelet is a wave-like oscillation with an amplitude that starts out at zero, increases, and then decreases back to zero. Unlike the sines used in Fourier transform for decomposition of a signal, wavelets are generally much more concentrated in time. They usually provide an analysis of the signal which is localized in both time and frequency, whereas Fourier transform is localized only in frequency. Examples for wavelets are given in Figure 3.3.

The original signal is transformed using predefined wavelets in wavelet transform. The wavelet transform is classified into Discrete Wavelet Transform and Continuous Wavelet Transform.

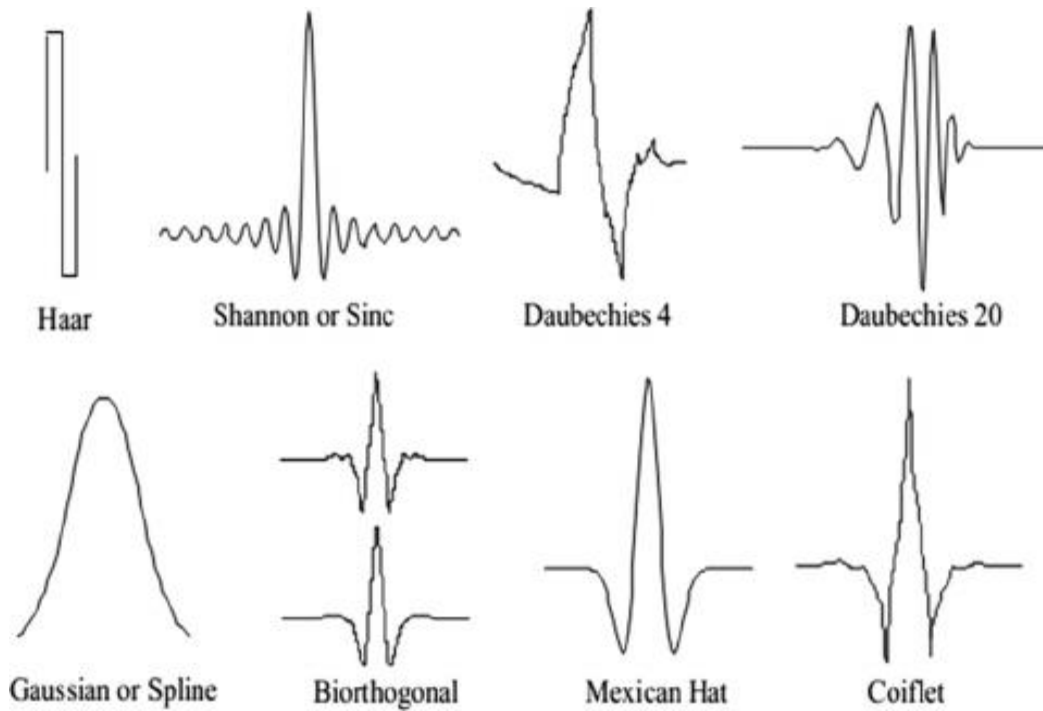


Fig 3. 3 Different wavelets used for wavelet transform

Given a mother wavelet $\psi(t)$ (which can be considered simply as a basis function of L^2), the continuous wavelet transform (CWT) of a function $x(t)$ (assuming that $x^2 \in L^2$) is defined as:

$$X(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi\left(\frac{t-b}{a}\right) x(t) dt \quad (1)$$

Mallat's Algorithm

In the case of DWT, assuming that the length of the signal satisfies $N = 2J$ for some positive J , the transform can be computed efficiently, using Mallat's algorithm [11], which has a complexity of $O(N)$. Essentially the algorithm is a fast hierarchical scheme for deriving the required inner products (which appear in (2.1), as a function of a and b) using a set of consecutive low and high pass filters, followed by a decimation. This

results in a decomposition of the signal into different scales which can be considered as different frequency bands. The low-pass (LP) and high-pass (HP) filters used in this algorithm are determined according to the mother wavelet in use. The outputs of the LP filters are referred to as approximation coefficients and the outputs of the HP filters are referred to as detail coefficients. Demonstration of the process of 3-level decomposition of a signal can be seen in Figure 3.4(below).

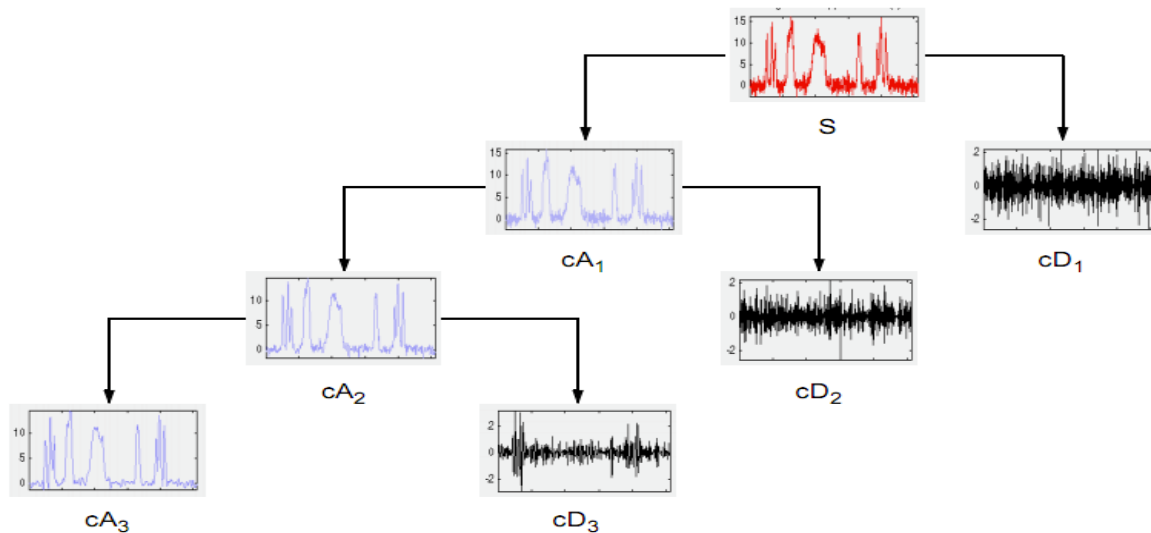


Fig 3. 4 Wavelet Decomposition at level 3

There are many types of wavelets they are, daubechies wavelet which is described by a maximal number of vanishing moments for some given support. In Haar wavelet which is an order of rescaled square shaped function which together to form a wavelet family. Symlet wavelets are an improved version of Daubechies wavelets with increased symmetry. Coiflets wavelets have scaling functions with vanishing moments. Signal reconstruction means reconstructing the original sequence from the thresholded wavelet detail coefficients leads to a denoised version of the original signal. Inverse Discrete Wavelet Transform (IDWT) is used to reconstruct the original signal. Therefore, wavelet transform is a reliable and better technique than Fourier transform technique.

Wavelet families

- **Daubachies:** Daubechies family wavelets are signed dbN (N is the order). This wavelet belongs to orthogonal wavelet.
- **Coiflets:** A discrete wavelets designed by Ingrid Daubechies to have a scaling function with vanishing moments. The scaling function and the wavelet function must be normalized by a common factor.
- **Symlet:** The symlet family wavelets are signed symN (N is the order). The symlets are nearly symmetrical, orthogonal and biorthogonal wavelets suggested by Daubechies as modifications to the db family. The properties of the two wavelet families are similar.
- **Biorthogonal:** Biorthogonal filters state a superset of orthogonal wavelet filters. The biorthogonal family wavelets are signed as bior. Biorthogonal wavelet transform has frequently been used in numerous image processing applications, because it makes possible multi-resolution analysis and does not produce redundant information

Some Application of Wavelets:

Wavelets are a powerful statistical tool which can be used for a wide range of applications, namely

- Signal processing
- Data compression
- Smoothing and image denoising
- Fingerprint verification
- DNA analysis

- Blood-pressure, heart-rate and ECG analyses
- Speech recognition
- Computer graphics and multifractal analysis

3.2.4 Baseline Drift Removal

Baseline correction belongs to one of the standard procedures in ERP research [3]. The sources of baseline wander may be different, but it always appears as a low-frequency artifact that introduces slow oscillations in the recorded signal. Baseline is due to brain activity, muscle tension, sweating, eye and head movements, electrode movement (in the case of EEG) or other noise sources [4].

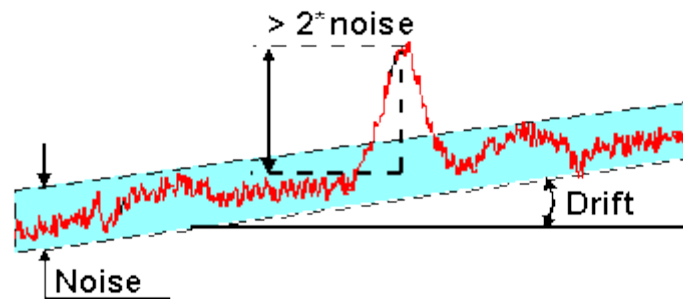


Fig 3. 5 Baseline Drift

Although baseline noise may be reduced by properly preparing skin and using suitable electrodes and electrode–gel combination, a preprocessing step for its removal is still required. In EOG detrending is achieved using a technique devised for ECG signals, which is based on wavelet decomposition. As observed in fig. 3.5 the baseline is seen to drift up due to the increase in the DC offset value. The change in the DC offset which makes it gradual rise/fall of the signal is known as Baseline drift.

3.2.5 Wavelet Denoising

Wavelets localize features in your data to different scales, you can preserve important signal or image features while removing noise. The

basic idea behind wavelet denoising, or wavelet thresholding, is that the wavelet transform leads to a sparse representation for many real-world signals and images. What this means is that the wavelet transform concentrates signal and image features in a few large-magnitude wavelet coefficients. Wavelet coefficients which are small in value are typically noise and you can "shrink" those coefficients or remove them without affecting the signal or image quality. After you threshold the coefficients, you reconstruct the data using the inverse wavelet transform.

The most general model for the noisy signal has the following form:

$$s(n) = f(n) + \sigma e(n) \quad (2)$$

where time n is equally spaced. In the simplest model, suppose that $e(n)$ is a Gaussian white noise $N(0,1)$, and the noise level σ is equal to 1. The denoising objective is to suppress the noise part of the signal s and to recover f .

The denoising procedure has three steps:

1. Decomposition — Choose a wavelet, and choose a level N . Compute the wavelet decomposition of the signal s at level N .
2. Detail coefficients thresholding — For each level from 1 to N , select a threshold and apply soft thresholding to the detail coefficients.
3. Reconstruction — Compute wavelet reconstruction based on the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N .

3.2.6 Median Filtering

Median filtering [5] is a common nonlinear method for noise suppression that has unique characteristics. It does not use convolution

to process the image with a kernel of coefficients. Rather, in each position of the kernel frame, a pixel of the input image contained in the frame is selected to become the output pixel located at the coordinates of the kernel center. The kernel frame is centered on each pixel (m, n) of the original image, and the median value of pixels within the kernel frame is computed. The pixel at the coordinates (m, n) of the output image is set to this median value. In general, median filters do not have the same smoothing characteristics as the mean filter [6]. Features that are smaller than half the size of the median filter kernel are completely removed by the filter. Large discontinuities such as edges and large changes in image intensity are not affected in terms of gray-level intensity by the median filter, although their positions may be shifted by a few pixels. This nonlinear operation of the median filter allows significant reduction of specific types of noise. For example, “pepper-and-salt noise” may be removed completely from an image without attenuation of significant edges or image characteristics. Figure 3.6 presents typical results of median filtering

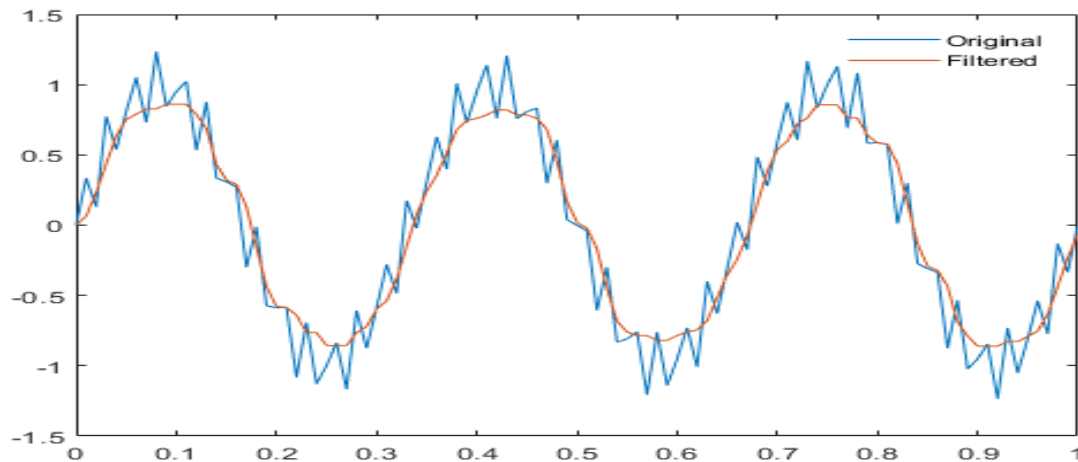


Fig 3. 6 Comparison between median filtered signal and the original signal

3.2.7 Moving Average

In statistics, a moving average (rolling average or running average) is a calculation to analyze data points by creating a series of averages of

different subsets of the full data set. It is also called a moving mean (MM) or rolling mean and is a type of finite impulse response filter. Variations include: simple, and cumulative, or weighted forms (described below).

Given a series of numbers and a fixed subset size, the first element of the moving average is obtained by taking the average of the initial fixed subset of the number series. Then the subset is modified by "shifting forward"; that is, excluding the first number of the series and including the next value in the subset.



Fig 3. 7 Simple Moving Average vs Exponential Moving Average vs Original Signal

A moving average is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. The threshold between short-term and long-term depends on the application, and the parameters of the moving average will be set accordingly. For example, it is often used in technical analysis of financial data, like stock prices, returns or trading volumes. It is also used in economics to examine gross domestic product, employment or other macroeconomic time series. Mathematically, a moving average is a type of convolution and so it can be viewed as an example of a low-pass filter used in signal

processing. When used with non-time series data, a moving average filters higher frequency components without any specific connection to time, although typically some kind of ordering is implied. Viewed simplistically it can be regarded as smoothing the data. Figure 3.7 demonstrates the process comparison.

3.3 Feature Extraction

3.3.1 Principal Component Analysis (PCA)

Principal component analysis (PCA) is the most widely used method for pattern recognition and feature extraction. It is used as the variable reduction procedure. PCA is used when there are a large number of variables and there occurs some redundancy in the variables. Redundancy means that some of the variables are correlated with one another. Due to this redundancy, it is possible to reduce the observed variables into a smaller number of principal components that will account for most of the variance in the observed variables. A principal component can be defined as a linear combination of optimally weighted observed variables. Principal Component Analysis (PCA) is used for analyzing data and finding the patterns. Principal Component Analysis, is a dominant tool for data compression and it projects higher dimensional data to lower dimensional data.

3.3.2 Independent Component Analysis (ICA)

The blind source separation has been widely used in many practical areas of modern signal processing. Based on the blind source separation, the independent source signals can be recovered after the signals are linearly mixed with an unknown medium and recorded at N sensors. The concept of independent component analysis (ICA) was described as

maximizing the degree of statistical independence among outputs using contrast functions approximated with the Edgeworth expansion of the Kullback-Leibler divergence. In contrast with de-correlation techniques such as Principal Component Analysis (PCA) which ensures that the output pairs are uncorrelated. ICA imposes the much stronger criterion that the multivariate probability density function of output variables factorizes. To find such a factorization, it is required that the mutual information between all variable pairs become zero. The decorrelation only takes account of second-order statistics, but the mutual information depends on all higher-order cumulants of the output variables [7].

To deal with the problem of EEG signal preprocessing, artifacts cancellation and source localization, it is always difficult due to the fact that the determination of brain electrical source from patterns collected from the scalp is mathematically underdetermined. Recent efforts to identify EEG sources have focused mostly on performing spatial segregation and localization of source activity. Using the ICA algorithm, the problem of both source identification and source localization have been investigated. The ICA algorithm derives independent sources from highly correlated EEG signals statistically and does not regard to the physical location or configuration of the source generators of EEG signals

3.4 Classification Techniques

3.4.1 Support Vector Machines (SVM)

Support vector machine is a machine learning model used for classification and regression analysis. When SVM is used for classification, they separate a given set of binary labeled training data and a hyperplane that is maximally distance from them. Assume the input data is $x^j = (x^{1j} \dots x^{nj})$ be the realization of the random vector x^j

While ϕ is the map mapping the feature space to a label space y , where label space contains many vectors, mathematically label as $\{(x^1, y^1), \dots(x^m, y^m)\}$. The SVM learning algorithm finds a hyperplane (w, b) such that the quantity

$$\gamma = \min_i y^i \{ \langle w, \phi(x^i) \rangle - b \} \quad (3)$$

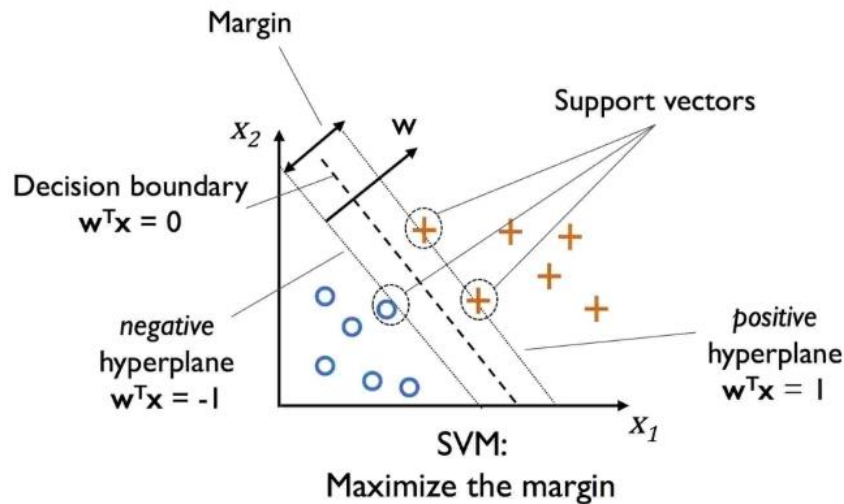


Fig 3. 8 Illustration of trained hyperplane

is maximized. In this equation, the dimension of ϕ is the same as the dimension of the label y and $\langle w, \phi(x^i) \rangle - b$ corresponds to the distance between point x^i and the decision boundary. γ is the margin and b is a real number. The kernel of this function is $K_{i,j} = \langle \phi(x^i), \phi(x^j) \rangle$. Given a new data x to classify, a label is assigned according to its relationship to the decision boundary, and the corresponding decision function is written as

$$f(x) = \text{sign}(\langle w, \phi(x) \rangle - b) \quad (4)$$

3.4.2 K-Nearest Neighbour (KNN)

K-NN classification is a non-parametric model that is described as instance-based learning which the model are characterized by

memorizing the training dataset [9]. KNN also a typical example of a lazy learner. It is called lazy not because of its apparent simplicity, but because it does not learn a discriminative function from the training data but memorized the training dataset instead. Lazy learning is a special case of instance-based learning that is associated with zero cost during the learning process. The k-NN algorithm is suitable to classify EEG data as it is a robust technique for large noisy data. The samples which is the data is classified by the majority vote of its neighbor's class. In order to determine the class, this algorithm requires training data and predefined k value as it will search through the training sample space for the k-most similar samples based on a similarity measure a distance function. The value of k and distance metric will affect the result of classification. Fig. 9 illustrates the concept of k-NN algorithm when applied the distance metric to determine the appropriate class of new data with $k = 9$. The data to be classified is at point $(0.6, 0.45)$, which is shown with "X". The big circle with dot line is represented the distance metric using Euclidean distance computation. It has two possible classes which is circle class with six instances and triangle class with three instances. The algorithm will classify mark "X" to the circle class as the circle class have the majority of data within the radius.

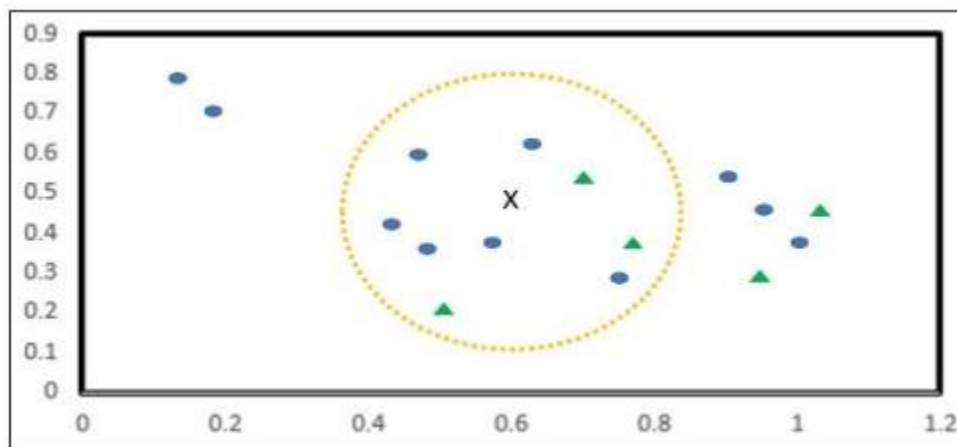


Fig 3. 9 KNN applied with $k = 9$

3.4.3 Artificial Neural Network (ANN)

Artificial Neural Network (ANN), a paradigm that is related to biological networks and tries to mimic the structure of the human brain [10]. A neural network is a massively equivalent distributed process, made up of simple processing units, which has a property for storing knowledge and making it available for use. One of the most important properties of neural networks is their ability to learn from examples, that is, learn to produce a certain output when fed with a certain input. The learning process involves modification of the connection weights, to make its overall performance correspond to a desired performance defined by the set of training examples.

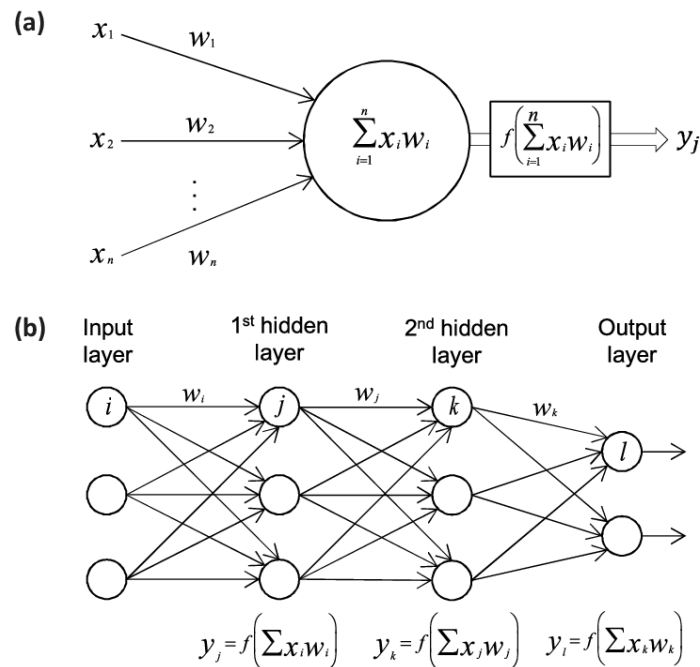


Fig 3. 10 (a) Operation of 1 neural unit of the neural network. Here f is predefined function known as an activation function. (b) 3-layer neural network

For each example in the training set there exists an input pattern and a desired output pattern. To train the network an example from the training set is chosen, and fed to the network to see what output it

produces. If the expected output is not obtained, the internal weights of the network is modified according to some training algorithm, so as to minimize the difference between the desired and the actual output. The training is then continued with another training example and so on, until the network has reached steady state. Here a fully connected network is employed and the standard back propagation algorithm can be used for training.

3.5 Review of applications using EEG

The advancement of technology has opened new gates to use EEG in many fields. As EEG map the neural activity of the brain, the information that is present in it is rich. If the information is extracted properly it will help us in many areas namely:

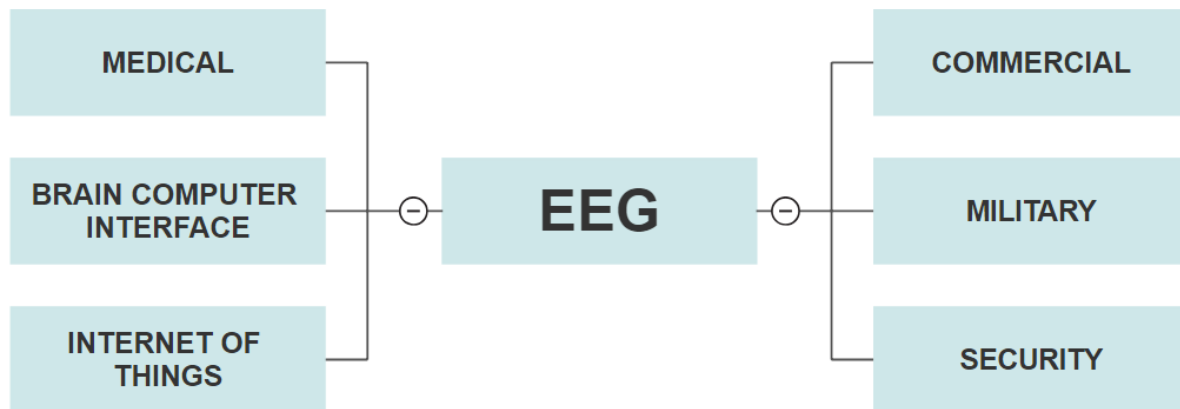


Table 3. 2 Block Diagram for EEG applications

3.5.1 Medical Applications

EEG was first applied in the medical field and now EEG is mostly used in this field for diagnostic and treatment purpose. It is used to predict the occurrence of epileptic seizure before its actual onset [12]. Yoga is beneficial both for the mind and the body. The scale of improvement is being studied by analyzing the change in the brain activity using EEG [13].

3.5.2 Commercial Applications

The consumer industry is using the information generated by EEG for analysis. The research is done on how to improve sales of their product for maximum profit. The Impact of advertisement on potential consumer is measured by measuring the response generated in EEG on certain advertisements [8]. The EEG signals of volunteers with varying age and gender were recorded while they browsed through various consumer products. The experiments were performed on the dataset comprised of various consumer products. The accuracy of choice prediction was recorded using a user-independent testing approach with the help of Hidden Markov Model (HMM) classifier [14]. Studies have demonstrated that anchors influence the economic valuation of various products and experiences. EEG experiment to investigate the anchoring effect on willingness to accept (WTA) for an aversive hedonic experience and the role of anchors in this judgment heuristic. The behavioral results demonstrated that random numbers affect participants' WTA for listening to pieces of noise [15]. The effect of different colours was analysed and it was found out that the various colors showed distinctly different effects on the mean power of the alpha band, theta band, and on the total power in the theta-beta EEG bandwidth and alpha attenuation coefficient (AAC) [16]

3.5.3 Military Applications

This is a new evolving field in terms of application of EEG. New sensors are being developed to enable research in this area. Low cost highly mobile EEG measuring devices are being developed to assess the stress level of soldier in the battle field real time [17] as illustrated in Fig 11. The assistance of computer in the battle field is being improved

using EEG signals so that soldier make split second decisions efficiently [18]



Fig 3. 11 A test system for assessing workload and engagement of computer gamers.

3.5.4 Brain Computer Interface (BCI)

Brain computer interface is one of the areas where EEG is being used the most. The signal generated from the EEG are being used to help the paralyze patients to be mobile again. This is done by developing devices that help assisting the user. Subjects with paralyzed legs use wheelchair to move but they need to depend on other for their mobility. With the help of EEG wave the wheel chair is being modified to be mind controlled so that user don't need to depend on other for their mobility [19].the system is illustrated in fig 12 Electroencephalography (EEG) signals have great impact on the development of assistive rehabilitation devices[20]. BCIs can classify EEG signals and translate the brain activities into useful commands for external devices [21]. Research is being done to make exoskeleton which can be mind controlled.

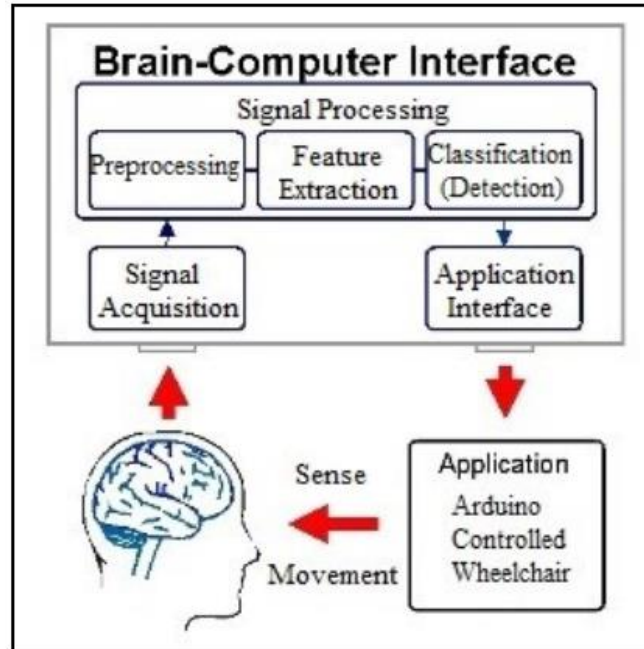


Fig 3. 12 Flow chart for mind controlled Wheelchair

The gaming industry is taking advantage of this technologies to develop games that are completely mind controlled. And thus can be played by anyone. It captures the signals and transfers them to the software that is responsible making them into action command.



Fig 3. 13 Mind controlled Gaming device

3.5.5 Internet of things(IOT)

- IOT is the next big innovation when it comes to making homes and the appliance involved it smarter. Research is done to control all the devices at home which simply the thought of it [22].

3.5.6 Security

- The issue of criminal activity has been an issue of great concern for years. EEG has given us a new perspective in analysing the criminal behavior so that correction facilities can better treat them and make them better human beings [23].

3.6 Summary

EEG has a wide range of techniques through which analysis is possible to delete the unwanted noise and bring out the useful information out of it before classifying it. Firstly, analysis of the signal is required. Fourier transform, wavelet transform are such techniques that give us an in depth view of the content of the signal. Secondly, depending on the application noise removal and removal of unimportant signals are implemented to take out the useful information for further processing. The techniques involved in this are Wavelet denoising, band pass filtering, median filtering etc. Different application requires different features extraction method. PCA, ICA, eigenvector, power of signal are good examples of feature extraction methods. The feature that are extracted can be used for classification. Some of the popular classification techniques involved are traditional method based classification, SVM, ANN, KNN, CNN etc. There are other techniques which are an ongoing field of research. EEG Signal preprocessing is one of the areas where research is being done in order to increase consistency of the signal.

References

1. Subha, D.P., Joseph, P.K., Acharya U, R. et al. J Med Syst (2010) 34: 195. <https://doi.org/10.1007/s10916-008-9231-z>
2. Al-Fahoum AS, Al-Fraihat AA. Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains. *ISRN Neurosci.* 2014;2014:730218. Published 2014 Feb 13. doi:10.1155/2014/730218
3. [arXiv:1707.08152v3](https://arxiv.org/abs/1707.08152v3) [stat.AP] [Phillip M. Alday](#) How much baseline correction do we need in ERP research? Extended GLM model can replace baseline correction while lifting its limits. (2019)
4. Antonio Fasano, Valeria Villani, Baseline wander removal for bioelectrical signals by quadratic variation reduction, *Journal Signal Processing* [archive](#) Volume 99, June, 2014 Pages 48-57 doi>[10.1016/j.sigpro.2013.11.033](https://doi.org/10.1016/j.sigpro.2013.11.033)
5. Raman B. Paranjape, Chapter 1 - Fundamental Enhancement Techniques, *Handbook of Medical Image Processing and Analysis* (Second Edition), Academic Press, 2009, Pages 3-18, ISBN 9780123739049, <https://doi.org/10.1016/B978-012373904-9.50008-8>.
6. Gonzalez RC, Wintz P. *Digital Image Processing*. Reading, MA: Addison-Wesley; 1987.
7. Lisha Sun, Ying Liu and P. J. Beadle, "Independent component analysis of EEG signals," *Proceedings of 2005 IEEE International Workshop on VLSI Design and Video Technology, 2005.*, Suzhou, China, 2005, pp. 219-222. doi:10.1109/IWVDVT.2005.1504590
8. Wei Zhen, Wu Chao, Wang Xiaoyi, Supratak Akara, Wang Pan, Guo Yike Using Support Vector Machine on EEG for Advertisement Impact Assessment *Frontiers in Neuroscience* (2018) volume 12 DOI=10.3389/fnins.2018.00076
9. Nurul E'zzati Md Isa,*, Amiza Amir, Mohd Zaizu Ilyas, and Mohammad Shahrazel Razalli "The Performance Analysis of K-Nearest Neighbors (K-NN) Algorithm for Motor Imagery Classification Based on EEG Signal" *MATEC Web of Conferences* 140, 01024 (2017) DOI: 10.1051/mateconf/201714001024
10. S. S. Lekshmi, V. Selvam and M. Pallikonda Rajasekaran, "EEG signal classification using Principal Component Analysis and Wavelet Transform with Neural Network," *2014 International Conference on Communication and Signal Processing*, Melmaruvathur, 2014, pp. 687-690. doi: 10.1109/ICCSP.2014.6949930
11. Moghim, N., & Corne, D. W. (2014). Predicting epileptic seizures in advance. *PloS one*, 9(6), e99334. doi:10.1371/journal.pone.0099334
12. Ganpat, T. S., Nagendra, H. R., & Selvi, V. (2013). Efficacy of yoga for mental performance in university students. *Indian journal of psychiatry*, 55(4), 349–352. doi:10.4103/0019-5545.120550
13. Yadava, M., Kumar, P., Saini, R. et al. *Multimed Tools Appl* (2017) 76: 19087. <https://doi.org/10.1007/s11042-017-4580-6>
14. Ma, Q., Li, D., Shen, Q., & Qiu, W. (2015). Anchors as Semantic Primes in Value Construction: An EEG Study of the Anchoring Effect. *PloS one*, 10(10), e0139954. doi:10.1371/journal.pone.0139954

15. Yoto, Ai & Katsuura, Tetsuo & Iwanaga, Koichi & Shimomura, Yoshihiro. (2007). Effects of Object Color Stimuli on Human Brain Activities in Perception and Attention Referred to EEG Alpha Band Response. *Journal of physiological anthropology*. 26. 373-9. 10.2114/jpa2.26.373.
16. R. Matthews *et al.*, "Real time workload classification from an ambulatory wireless EEG system using hybrid EEG electrodes," *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Vancouver, BC, 2008, pp. 5871-5875. doi: 10.1109/IEMBS.2008.4650550
17. Stephen M. Gordon, Matthew Jaswa, Amelia J. Solon, and Vernon J. Lawhern. 2017. Real World BCI: Cross-Domain Learning and Practical Applications. In *Proceedings of the 2017 ACM Workshop on An Application-oriented Approach to BCI out of the laboratory (BCIforReal '17)*. ACM, New York, NY, USA, 25-28. DOI: <https://doi.org/10.1145/3038439.3038444>
18. I. A. Mirza *et al.*, "Mind-controlled wheelchair using an EEG headset and arduino microcontroller," *2015 International Conference on Technologies for Sustainable Development (ICTSD)*, Mumbai, 2015, pp. 1-5. doi: 10.1109/ICTSD.2015.7095887
19. AL-Quraishi, Maged S. and Elamvazuthi, Irraivan and Daud, Siti Asmah and Parasuraman, S. and Borboni, Alberto, "EEG-Based Control for Upper and Lower Limb Exoskeletons and Prostheses: A Systematic Review" , *Sensors*, VOLUME 18, (2018), 10, <http://www.mdpi.com/1424-8220/18/10/3342>
20. Konstantinidis, Evdokimos & Conci, Nicola & Bamparopoulos, Giorgos & A. Sidiropoulos, Efstathios & De Natale, Francesco & Bamidis, Panagiotis. (2015). Introducing Neuroberry, a platform for pervasive EEG signaling in the IoT domain. 10.4108/eai.14-10-2015.2261698.
21. Konstantinidis, Evdokimos & Conci, Nicola & Bamparopoulos, Giorgos & A. Sidiropoulos, Efstathios & De Natale, Francesco & Bamidis, Panagiotis. (2015). Introducing Neuroberry, a platform for pervasive EEG signaling in the IoT domain. 10.4108/eai.14-10-2015.2261698.
22. Pillmann F, Rohde A, Ullrich S, Draba S, Sannemüller U, Marneros A. "Violence, criminal behavior, and the EEG: significance of left hemispheric focal abnormalities." *J Neuropsychiatry Clin Neurosci*. 1999 Fall;11(4):454-7. DOI: 10.1176/jnp.11.4.454

Chapter 4: *Software and Hardware Required for capturing and analyzing EEG*

4.1 Introduction

EEG signal received in scalp area is in 10-100 μ V range. Therefore, sophisticated hardware is required to record, amplify and filter the signal. Searching the internet, we found OPENBCI [1] is the most readily available design that can be printed with 3D printers and there is also an option to buy it. Next in list is Emotivepoc+ [2]. It comes with wireless transaction facility and multiple channel support. Con with this setup is one need to subscribe for the interfacing software package also. Next we found some Indian manufacturer who are making medical grade EEG systems as RMSIndia [3]. We choose Axxonet Pvt. Ltd. and used there 32 channel EEG acquisition system for our project [4]. They have 16-256 channel EEG acquisition systems. For software we primarily used Matlab with EEGLAB Toolbox. We also considered Python with EDFLIB package to analysis the signal which is discussed in the chapter.

4.2 EEG acquisition: Axxonet's Brain Electro Scan System (BESS)

Having been developed for research purposes, BESS is equipped with a user-friendly stimulus presentation package, capable of presenting stimuli in visual and auditory modality, with unique provisions for customizing its stimulus presentation properties [5][6].

- BESS provides a comprehensive Stimulus presentation package that automates functions related to ERP presentation from Presentation to Analysis, the first of its kind. *In addition, BESS interfaces with tools such as E-Prime and OpenSesame.*

- The **xAmp** series of amplifiers have 8 to 128 Channels, 24-bit resolution with simultaneous sampling of 20KHz per channel in select models. With a low noise floor of <1 uV the xAmp series ensure high quality recordings.
- **xAmp** can interface with third party headsets and headgear including active electrodes.
- **xAmp** has direct interfaces with Axxonet's innovative RapidCap, the new ultra-fast deployment multi contact eeg cap that supports Saline and Gel recordings.
- BESS has built-in digital EEG data processing capabilities that are complex, yet accurate and only found in solutions like Octave or Matlab.
- Its advanced analysis package makes BESS a complete and one of the finest ERP tools for research in the area of neuroscience, be it cognitive science, neuropsychology or electrophysiology.
- BESS is highly sophisticated, user friendly system developed for acquisition and analysis of bioelectrical brain activity.
- It is employed in research under neuroscience, cognitive psychology, cognitive science, and psycho-physiology. It is available in Auditory and Visual modalities.
- The systems are highly accurate with complex data processing and analysis capabilities. The systems are built over years of research and development in the field of Electroencephalography.
- BESS is available in Desktop and Laptop versions for mobile recordings.
- B.E.S.S. Models are available in 16, 32, 64, 128, and 256 channel configurations and can be built customized as per requirements.
- Provisions are available to customize it as per the requirement for clinical application and diagnosis as well.

EEG - ERP Recordings:

- Ability to treat each stimulus as an Event with additional keyboard events
- Ability to mark beginnings and end of Stimulus, Prestimulus duration
- Group batch of Stimulus into bins
- Edit event makers and save as new file

The B.E.S.S. Clinical Models are available in 16, 32, 64, 128, and 256 channel configurations and can be built customized as per requirements

The systems are available in desktop versions and laptop versions.

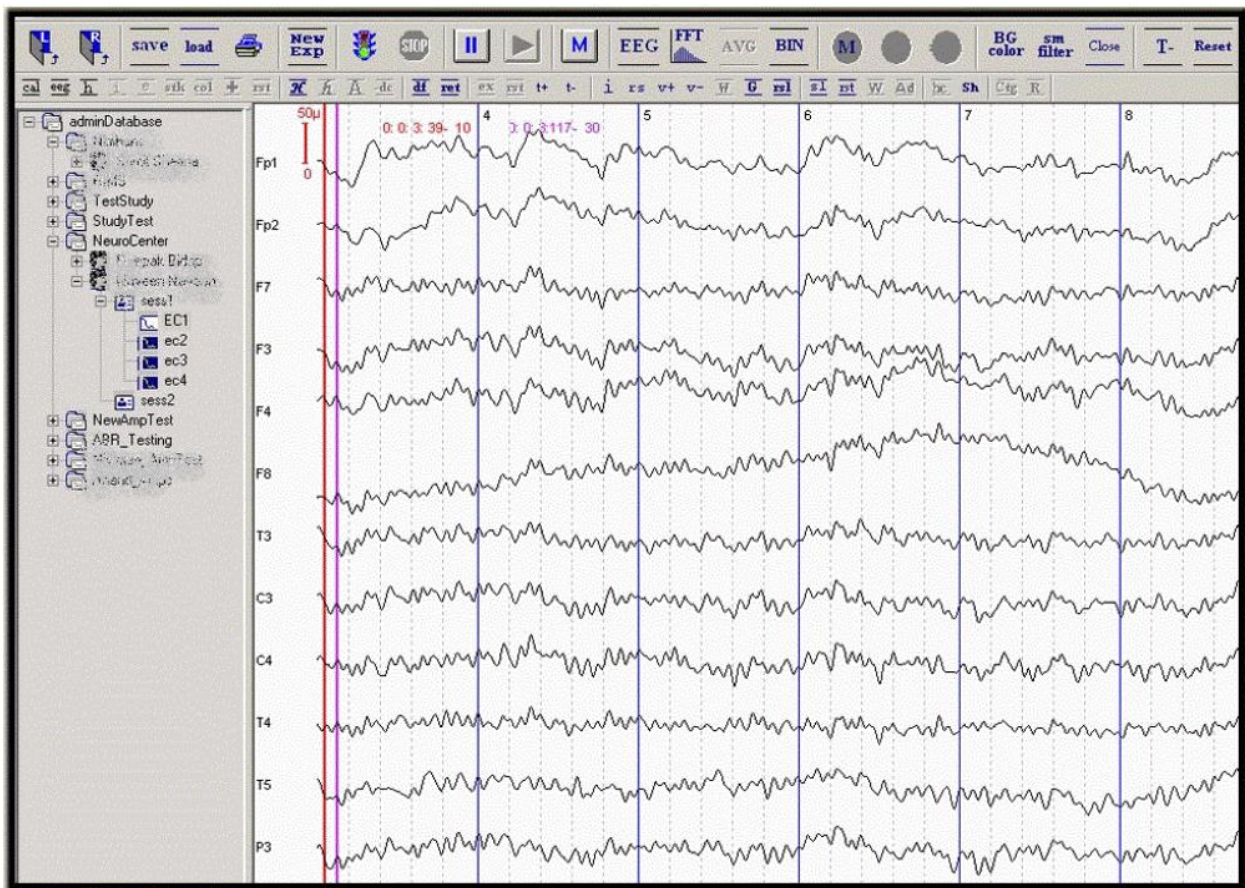


Fig 4. 1 EEG acquisition in real time using BESS

4.3 Analyzing EEG: Softwares Required

4.3.1 Matlab 2014a

MATLAB® [7] is the high-level language and interactive environment used by millions of engineers and scientists worldwide. It lets you explore and visualize ideas and collaborate across disciplines including signal and image processing, communications, control systems, and computational finance. MATLAB can be used to run millions of simulation to pinpoint optimal dosing for antibiotics.

4.3.1.1 Key Features

- High-level language for numerical computation, visualization, and application development
- Interactive environment for iterative exploration, design, and problem solving
- Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, numerical integration, and solving ordinary differential equations
- Built-in graphics for visualizing data and tools for creating custom plots
- Development tools for improving code quality and maintainability and maximizing performance
- Tools for building applications with custom graphical interfaces
- Functions for integrating MATLAB based algorithms with external applications and languages such as C, Java, .NET, and Microsoft® Excel. ®

4.3.1.2 Functions

Numeric Computation MATLAB provides a range of numerical computation methods for analyzing data, developing algorithms, and creating models. The MATLAB language includes mathematical functions that support common engineering and science operations. Core

math functions use processor optimized libraries to provide fast execution of vector and matrix calculations.

Available methods include:

1. Interpolation and regression
2. Differentiation and integration
3. Linear systems of equations
4. Fourier analysis
5. Eigen values and singular values
6. Ordinary differential equations (ODEs)
7. Sparse matrices
8. Wavelet Analysis

4.3.1.3 Data Analysis and Visualization

MATLAB provides tools to acquire, analyze, and visualize data, enabling you to gain insight into your data in a fraction of the time it would take using spreadsheets or traditional programming languages. You can also document and share your results through plots and reports or as published MATLAB code.

4.3.1.4 Acquiring Data

MATLAB lets you access data from files, other applications, databases, and external devices. You can read data from popular file formats such as Microsoft Excel; text or binary files; image, sound, and video files; and scientific files such as net, CDF and HDF. File I/O functions let you work with data files in any format. Using MATLAB with add-on products, you can acquire data from hardware devices, such as your computer's serial port or sound card, as well as stream live, measured data directly into MATLAB for analysis and visualization. You can also communicate with instruments such as oscilloscopes, function generators, and signal analyzers.

4.3.1.5 Analyzing Data

MATLAB lets you manage, filter, and preprocess your data. You can perform exploratory data analysis to uncover trends, test assumptions, and build descriptive models. MATLAB provides functions for filtering and smoothing, interpolation, convolution, and fast Fourier transforms (FFTs). Add-on products provide capabilities for curve and surface fitting, multivariate statistics, spectral analysis, image analysis, system identification, and other analysis tasks.

4.3.1.6 Visualizing Data

MATLAB provides built-in 2-D and 3-D plotting functions, as well as volume visualization functions. You can use these functions to visualize and understand data and communicate results. Plots can be customized either interactively or programmatically. The MATLAB plot gallery provides examples of many ways to display data graphically in MATLAB. For each example, you can view and download source code to use in your MATLAB application.

4.3.1.7 Documenting and Sharing Results

You can share results as plots or complete reports. MATLAB plots can be customized to meet publication specifications and saved to common graphical and data file formats. You can automatically generate a report when you execute a MATLAB program. The report contains your code, comments, and program results, including plots. Reports can be published in a variety of formats, such as HTML, PDF, Word, or LaTeX.

4.3.1.8 Programming and Algorithm Development

MATLAB provides a high-level language and development tools that let you quickly develop and analyze algorithms and applications.

4.3.1.9 Application Development and Deployment

MATLAB tools and add-on products provide a range of options to develop and deploy applications. You can share individual algorithms and applications with other MATLAB users or deploy them royalty-free to others who do not have MATLAB.

4.3.1.10 Designing Graphic User Interface

Using GUIDE (Graphical User Interface Development Environment), you can lay out, design, and edit custom graphical user interfaces. You can include common controls such as list boxes, pull-down menus, and push buttons, as well as MATLAB plots. Graphical user interfaces can also be created programmatically using MATLAB functions.

4.3.1.11 Generating C Code

You can use MATLAB Coder to generate standalone C code from MATLAB code. MATLAB Coder supports a subset of the MATLAB language typically used by design engineers for developing algorithms as components of larger systems. This code can be used for standalone execution, for integration with other software applications, or as part of an embedded application.

4.3.1.12 Development Tools

MATLAB includes a variety of tools for efficient algorithm development, including:

1. Command Window - Lets you interactively enter data, execute commands and programs, and display results
2. MATLAB Editor - Provides editing and debugging features, such as setting break points and stepping through individual lines of code.
3. Code Analyser - Automatically checks code for problems and recommends modifications to maximize performance and maintainability
4. MATLAB Profiler - Measures performance of MATLAB programs and identifies areas of code to modify for improvement.

4.3.1.13 Syntax

The MATLAB application is built around the MATLAB language, and most use of MATLAB involves typing MATLAB code into the Command Window (as an interactive mathematical shell), or executing text files containing MATLAB code, including scripts and/or functions.

4.3.1.14 Variables

Variables are defined using the assignment operator, =. MATLAB is a weakly typed programming language because types are implicitly converted. It is an inferred typed language because variables can be assigned without declaring their type, except if they are to be treated as symbolic objects, and that their type can change. Values can come from constants, from computation involving values of other variables, or from the output of a function.

4.3.1.15 Matrices

Matrices can be defined by separating the elements of a row with blank space or comma and using a semicolon to terminate each row. The list of elements should be surrounded by square brackets: []. Parentheses: () are used to access elements and sub arrays (they are also used to denote a function argument list).

4.3.1.16 Structures

MATLAB has structure data types. Since all variables in MATLAB are arrays, a more adequate name is "structure array", where each element of the array has the same field names. In addition, MATLAB supports dynamic field names (field look-ups by name, field manipulations, etc.). Unfortunately, MATLAB JIT does not support MATLAB structures; therefore, just a simple bundling of various variables into a structure will come at a cost.

4.3.1.17 GUI Programming

MATLAB supports developing applications with graphical user interface features. MATLAB includes GUIDE (GUI development environment) for graphically designing GUIs. It also has tightly integrated graph-plotting features.

4.3.1.18 Applications

1. Data Exploration, Acquisition, Analyzing & Visualization
2. Engineering drawing and Scientific graphics

3. Analyzing of algorithmic designing and development
4. Mathematical functions and Computational functions
5. Simulating problems prototyping and modeling
6. Application development programming using GUI building environment.

4.4 EEGLAB TOOLBOX

EEG signal is saved in European Data Format (.edf) which cannot be opened directly in Matlab. EEGLAB [8] toolbox provide support for reading different format of EEG file and plot them with analyzing different useful inbuilt functions. EEGLAB is an interactive Matlab toolbox for processing continuous and event-related EEG, MEG and other electrophysiological data incorporating independent component analysis (ICA), time/frequency analysis, artifact rejection, event-related statistics, and several useful modes of visualization of the averaged and single-trial data. EEGLAB runs under Linux, Unix, Windows, and Mac OS.

EEGLAB provides an interactive graphic user interface (GUI) allowing users to flexibly and interactively process their high-density EEG and other dynamic brain data using independent component analysis (ICA) and/or time/frequency analysis (TFA), as well as standard averaging methods. EEGLAB also incorporates extensive tutorial and help windows, plus a command history function that eases users' transition from GUI-based data exploration to building and running batch or custom data analysis scripts. EEGLAB offers a wealth of methods for visualizing and modeling event-related brain dynamics, both at the level of individual EEGLAB 'datasets' and/or across a collection of datasets brought together in an EEGLAB 'studysset.'

For experienced Matlab users, EEGLAB offers a structured programming environment for storing, accessing, measuring, manipulating and visualizing event-related EEG data. For creative research programmers and methods developers, EEGLAB offers an extensible, open-source platform through which they can share new methods with the world research community by publishing EEGLAB 'plug-in' functions that appear automatically in the EEGLAB menu of users who download them. For example, novel EEGLAB plug-ins might be built and released to 'pick peaks' in ERP or time/frequency results, or to perform specialized import/export, data visualization, or inverse source modeling of EEG, MEG, and/or ECOG data. Figure 4.2 demonstrates EEGLAB GUI window opened in Matlab.

4.4.1 EEGLAB Features

- Graphic user interface
- Multi-format data importing
- High-density data scrolling
- Interactive plotting functions
- Semi-automated artifact removal
- ICA & time/frequency transforms
- Event & channel location handling
- Forward/inverse head/source modeling
- Defined EEG data structure
- Many advanced plug-in/extension toolboxes

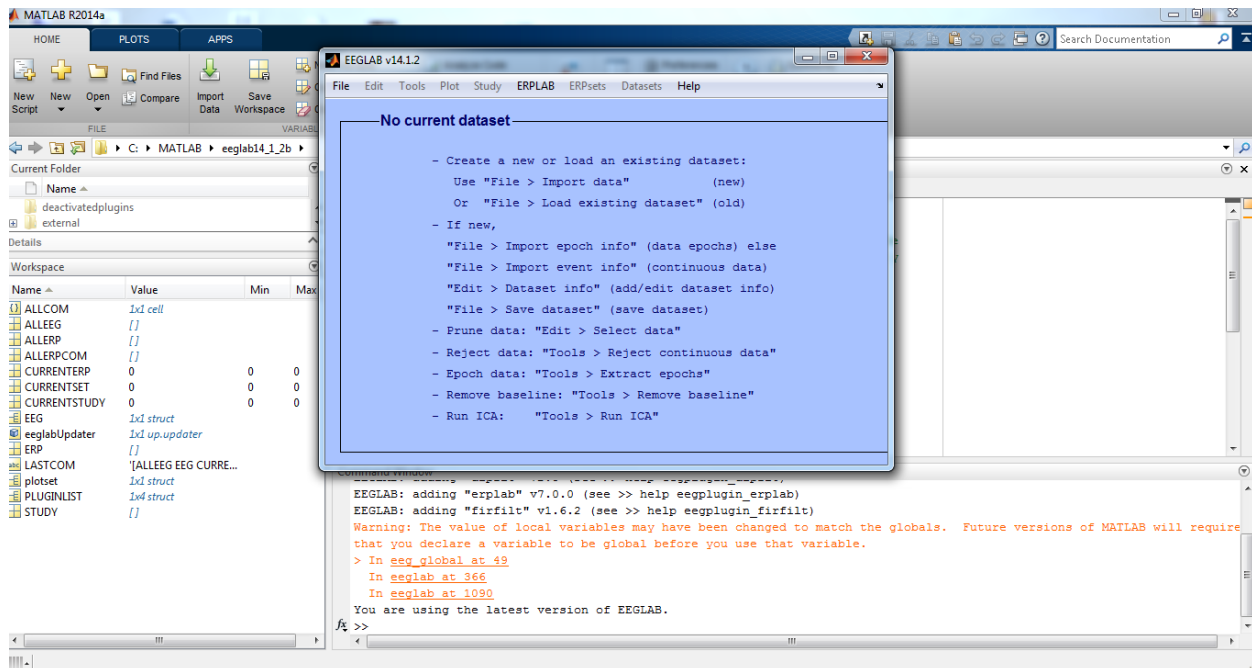


Fig 4. 2 EEGLAB GUI window in Matlab

4.4.2 EEGLAB System Requirements

Matlab version: The latest version of EEGLAB runs on Matlab 7.6 (2008b) or later under any operating system (Linux/Unix, Windows, Mac OSX). For earlier Matlab version, download legacy version EEGLAB v4.3 which will run on Matlab 5.3. EEGLAB extensions (in particular BCILAB and SIFT) also require Matlab 7.6 or later. Note that all EEGLAB signal processing functions also runs on the free Matlab clone Octave although graphics cannot be displayed (this is useful for high performance computing application - see the [EEGLAB wiki](#) for more details).

Memory requirements: Using multi-core 64-bit processors with large amounts of RAM may be essential for analyzing large datasets -- 8 Gb or more RAM is recommended (also see the EEGLAB wiki tutorial for tips on minimizing memory usage). Linux is to be preferred as an environment for processing EEG data using EEGLAB, mostly because

of better memory management of Matlab under Linux (if using Linux, choose Fedora over Ubuntu as there are sometimes minor graphics problem with how Matlab handles OpenGL under Ubuntu).

Additional Matlab toolboxes: EEGLAB requires no additional toolboxes. However, some toolboxes are recommended. By order of importance,

- *Signal Processing toolbox:* although EEGLAB incorporates functions to replace functions it uses from this toolbox when necessary (e.g., for filtering and power spectra computation), they are not as efficient as the toolbox Matlab functions. This toolbox is also required by some EEGLAB extensions such as SIFT. This is probably the most important toolbox to have.
- *Statistics toolbox:* this toolbox is required by some EEGLAB extensions (such as Fieldtrip and SIFT). This toolbox also contains a large number of functions useful for the advanced programmer to compute statistics and cross-validation.
- *Optimization toolbox:* another recommended toolbox used by some EEGLAB extensions. This toolbox contains the powerful fmin search function and derivative. Although Matlab now has this function by default in its core distribution, the optimization toolbox allows to perform finer tuning of its parameters.
- *Image processing toolbox:* this toolbox is required by some EEGLAB extensions (such as Fieldtrip).

Figure post processing: After figures are exported in the postscript vector format from Matlab/EEGLAB, a postscript editor is usually necessary to fine tune them for publication.

- MIT to EDF+ converter (including annotations) for [Physiobank](#)
- Manscan Microamps (*.mbi/*.mb2) to EDF+ converter (including annotations)
- SCP-ECG (*.scp, EN 1064) to EDF+ converter
- Synchronous video playback
- Emsa (*.PLG) to EDF+ converter (including annotations)
- ASCII to EDF/BDF converter
- Finometer (Beatscope) to EDF converter
- Bmeye Nexfin (FrameInspector) to EDF converter
- WAV to EDF converter
- Mortara XML ECG to EDF converter
- reads Biosemi's trigger inputs from the BDF "Status" signal
- Annotation editor
- Header editor, fixes also lots of different format-errors
- 1th to 8th order Butterworth, Chebyshev, Bessel and "moving average" filters
- Notch filter with adjustable Q-factor
- Customizable FIR filter
- Spike filter removes spikes, glitches, fast transients or pacemaker impulses.
- Power spectrum (FFT)
- ECG Heart Rate detection (raw ECG waveform -> beats per minute)
with possibility to export the RR-intervals (beat to beat)
- FM modulated (transtelephonic) ECG recording to EDF converter
- Z-EEG measurement

- Averaging using triggers, events or annotations
- Supports montages
- Annotations/events export
- Annotations/events import
- File reducer/cropper/decimator
- Down sampling signals
- Precise measurements by using crosshairs
- Zoom function by drawing a rectangle with the mouse
- Shows signals from different files at the same time
- EDF/EDF+/BDF/BDF+ to ASCII converter
- EDF/EDF+/BDF/BDF+ compatibility checker
- EDF+D to EDF+C converter
- BDF (+) to EDF (+) converter
- Prints to a printer, image or PDF
- Combine several files and export it to one new EDF file
- Export a part of a file to a new file
- Reads from a streaming file (monitor)
- Available for Linux and Windows (the source can be compiled on Mac OS X)

4.6 Python

Python is a general-purpose interpreted, interactive, object-oriented, and high-level programming language. It was created by Guido van Rossum during 1985- 1990. Like Perl, Python source code is also available under the GNU General Public License (GPL). Python's design philosophy emphasizes code readability with its notable use of significant

whitespace. Its language constructs and object-oriented approach aims to help programmers write clear, logical code for small and large-scale projects. [10] Van Rossum shouldered sole responsibility for the project until July 2018 but now shares his leadership as a member of a five-person steering council. Figure 4.4 describes a python terminal window.

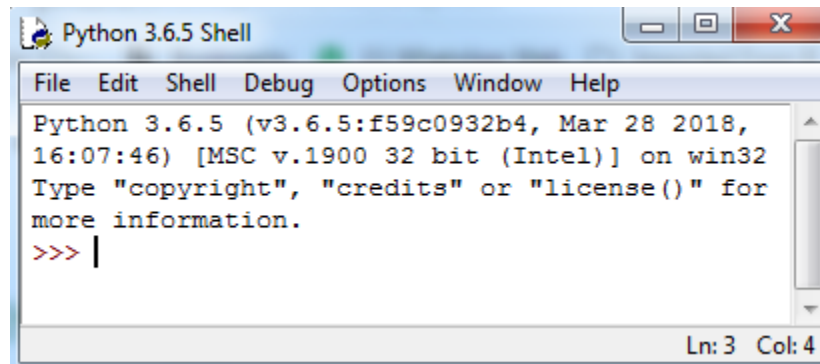


Fig 4. 4 Python Shell Terminal

4.6.2 Python Features

Python's features include –

- **Easy-to-learn** – Python has few keywords, simple structure, and a clearly defined syntax. This allows the student to pick up the language quickly.
- **Easy-to-read** – Python code is more clearly defined and visible to the eyes.
- **Easy-to-maintain** – Python's source code is fairly easy-to-maintaining.
- **A broad standard library** – Python's bulk of the library is very portable and cross-platform compatible on UNIX, Windows, and Macintosh.

- **Interactive Mode** – Python has support for an interactive mode which allows interactive testing and debugging of snippets of code.
- **Portable** – Python can run on a wide variety of hardware platforms and has the same interface on all platforms.
- **Extendable** – You can add low-level modules to the Python interpreter. These modules enable programmers to add to or customize their tools to be more efficient.
- **Databases** – Python provides interfaces to all major commercial databases.
- **GUI Programming** – Python supports GUI applications that can be created and ported to many system calls, libraries and windows systems, such as Windows MFC, Macintosh, and the X Window system of Unix.
- **Scalable** – Python provides a better structure and support for large programs than shell scripting.

Apart from the above-mentioned features, Python has a big list of good features, few are listed below –

- It supports functional and structured programming methods as well as OOP.
- It can be used as a scripting language or can be compiled to byte-code for building large applications.
- It provides very high-level dynamic data types and supports dynamic type checking.
- It supports automatic garbage collection.
- It can be easily integrated with C, C++, COM, ActiveX, CORBA, and Java.

4.6.3 Relevant libraries in python

4.6.3.1 pyEDFlib

pyEDFlib is a python library to read/write EDF+/BDF+ files based on EDFlib [11]. EDF means European Data Format and was firstly published Kemp1992. In 2003, an improved version of the file protokoll named EDF+ has been published and can be found at Kemp2003.

The EDF/EDF+ format saves all data with 16 Bit. A version which saves all data with 24 Bit, was introduces by the company BioSemi.

The definition of the EDF/EDF+/BDF/BDF+ format can be found under edfplus.info.

This python toolbox is a fork of the toolbox from Christopher Lee-Messer and uses the EDFlib from Teunis van Beelen. The EDFlib is able to read and write EDF/EDF+/BDF/BDF+ files.

Documentation

Documentation is available online at <http://pyedflib.readthedocs.org>

Installation

pyEDFlib can be used with Python 2.7.x or ≥ 3.4 . It depends on the Numpy package. To use the newest source code from git, you have to download the source code. You need a C compiler and a recent version of Cython. Go then to the source directory and type:

```
python setup.py build
```

```
python setup.py install
```

There are binary wheels which can be installed by:

```
pip install pyEDFlib
```


Users of the Anaconda Python distribution can directly obtain pre-built Windows, Intel Linux or macOS / OSX binaries from the conda-forge channel. This can be done via:

conda install -c conda-forge pyedflib

The most recent *development* version can be found on GitHub at <https://github.com/holgern/pyedflib>. The latest release, including source and binary packages for Linux, macOS and Windows, is available for download from the Python Package Index. You can find source releases at the Releases Page.

License

pyEDFlib is a free Open Source software released under the BSD 2-clause license.

4.6.3.2 Numpy

NumPy is the fundamental package for scientific computing with Python [12]. It contains among other things:

- a powerful N-dimensional array object
- sophisticated (broadcasting) functions
- tools for integrating C/C++ and Fortran code
- useful linear algebra, Fourier transform, and random number capabilities

Besides its obvious scientific uses, NumPy can also be used as an efficient multi-dimensional container of generic data. Arbitrary data-types can be defined. This allows NumPy to seamlessly and speedily integrate with a wide variety of databases. NumPy is licensed under the BSD license, enabling reuse with few restrictions.

Getting Started

To install NumPy, we strongly recommend using a *scientific Python distribution*. See Installing the SciPy Stack for details. Many high quality online tutorials, courses, and books are available to get started with NumPy. We also recommend the SciPy Lecture Notes for a broader introduction to the scientific Python ecosystem. For more information on the SciPy Stack (for which NumPy provides the fundamental array data structure), see scipy.org.

Documentation

The most up-to-date NumPy documentation can be found at Latest (development) version. It includes a user guide, full reference documentation, a developer guide, meta information, and “NumPy Enhancement Proposals” (which include the NumPy Roadmap and detailed plans for major new features).

A complete archive of documentation for all NumPy releases (minor versions; bug fix releases don't contain significant documentation changes) since 2009 can be found at <https://docs.scipy.org>.

4.7 Summary

The above mentioned tools are highly sophisticated and recommended for EEG related studies. Although there are a lot of resources available over the internet. For example, Biosig, Bioelectromagnetism, Fieldtrip, Brainstorm, Brain Vision Analyzer etc. are preferable tools for analyzing EEG data using Matlab. Where as in python one can use PYEEG, MNE tools, NeuroPy etc. Most of this tools are open source. MNE tools website has a lot of experimental EEG data available to download to give a head start.

References:

1. <https://openbci.com>
2. <https://www.emotiv.com>
3. <http://www.rmsindia.com/neurology.html>
4. <https://www.axxonet.com/medical/13-medical/27-brain-electro-scan-system-bess-eeg-erp-systems>
5. <https://www.axxonet.com/medical/13-medical/27-brain-electro-scan-system-bess-eeg-erp-systems>
6. <https://www.youtube.com/watch?v=BX3MG2yFBuY>
7. <https://in.mathworks.com/help/matlab/release-notes-R2014a.html>
8. <https://scn.ucsd.edu/eeglab/index.php>
9. <https://www.teuniz.net/edfbrowser>
10. Kuhlman, Dave. "A Python Book: Beginning Python, Advanced Python, and Python Exercises". Section 1.1. Archived from the original (PDF) on 23 June 2012.
11. <https://pypi.org/project/pyEDFlib/>
12. <https://www.numpy.org>

Chapter 5: *Data Acquisition*

5.1 Introduction

EEG Data acquisition is one of the vital steps of the whole processing step. Many research analysts say “there is no substitute for clean data”. There are certain protocols to be followed in order to perform data acquisition as efficiently as possible. It is quite evident that the EEG is susceptible to noise as there are multiple sources of it. If proper measures are taken, then some of the noise sources might be prevented from affecting the signal of interest. the resolution of the data can be varied based on the application. the resolution is defined by the number of EEG probes that are placed on the subjects’ head for measurement. It can range from as low as 2 channel to as high as 256 channel. More number of channels gives us a deeper insight and richer information about the activity of the brain. The electrodes used for recording can be varied based on the precision. As the raw EEG signal has a wide range of frequency, the choice of frequency is also important. The frequency range of EEG is from 1 to 50 Hz. Thus based the application the frequency needs to be filtered.



Fig : 1 256 channel EEG cap

5.2 BASIC PROTOCOL: Preparation of Human Subjects for EEG Studies

Before we advertise the experiment and gather participants, we have to decide on subject criteria. Selected subjects have to meet all pre-determined requirements. Those are designed to match the hypotheses, laws and ethical regulations. The requirements that match the hypotheses differ from experiment to experiment. The requirements that match laws and regulations are common for all EEG experiments. Those ensures safety for all participants.

Common selection criteria are:

- General good health,
- No pregnancy,
- No claustrophobia,
- No drug addiction,
- No neurological diseases.

Specific selection criteria that differs from experiment to experiment to take into account:

- Range of age,
- One or both genders,
- Academic level,
- Specific type of disease or the absence of it (in case of studies on dementia or other diseases),
- Visual acuity and/or hearing acuity (depending on the type of stimuli which subjects are exposed to during the experiment),
- If the person is left handed or right handed.

5.3 Subjects Data Selection

The data gathered is not always clear enough to process as mentioned earlier. Some of the reasons to reject a subject after recording are:

- lack of signal for a specific time window,
- external sudden electrical noises that ruin the signal,
- electrodes shifting or falling due to subject mis-comfort that cause the signal to drop.
- Improper gelling of the contact between the scalp and the electrodes.

It is recommended to check the data before starting processing. In case of missing data, the subject can be rejected or brought in again for additional tests or minor adjustments can be made to restore proper collection of the data.

5.4 EEG acquisition setup block

Fig. 5.1 shows the general block for acquiring the signal during an experiment using visual or auditory evoked potentials.

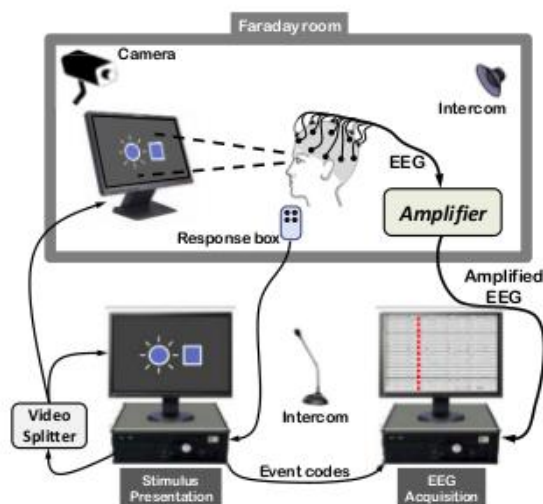


Fig 5. 1 EEG Acquisition setup

Amplifier amplifies the signal to make the signal in the range of μV readable to user it also performs frequency filtering if asked.

- the stimulus presenter is used to show the presentation of the task the user is given. the response box is a set of keys that the user can press if the task requires the used to do so.
- camera is used to record the subject's behavior. and if possible do eye tracking if required.

5.5 Experimental Procedure

Recruiting subjects

- Advertise the experiments and the subjects' requirements within fellow research groups, hospitals, and medical centers.
- Screen possible choices and arrange appointment for testing.
- Instruct the subject to come to the test with just washed hair and no hair products, and to be on their best physical and mental conditions.

Before the experiment

- Prepare information notice, instruction paper and consent paper,
- verify and test the setup, the stimulation system and routine, the hardware in the workspace,
- check connection with recording system,
- Prepare your gel syringes if you are using wet electrodes.

During the experiment

- Welcome the subject in the lab, make them feel comfortable,
- explain the experiment and make sure the subject is clear on any aspect of it,
- have subject sign the consent paper,

- adjust the stimulation set up to subject comfort (adjust chair height, screen distance or check sound),
- prepare head and secure selected cap,
- perform impedance measurement,
- perform testing,
- verify the obtained signal is properly electrophysiological,
- keep the subject attentive and motivated, allow for breaks.

In our experiment, Axxonet's Brain Electro Scan System (BESS) which is a 32 channel EEG system, was used to record the EEG data of the subjects. The system has maximum sampling rate per channel of 30kps and runs on 5V AC supply. Gold plated silver electrodes soaked in saline water were used. The detection of Beta waves (16-31 Hz) which is responsible for cognitive actions like thinking, planning, focusing, high alert etc., is profoundly observed over the recorded data. Initially notch filter of 0.5 to 75 Hz was applied. T8, CP6, A1, A2 channels were used to record EOG data. 10-20 electrode placement system is used to record EEG data. Depicted below in Figure 1 and Figure 2 is the cross sectional view of the electrode placement to capture the EEG and one of the subject while capturing the EEG data respectively.

5.6 EOG Data Acquisition

Before starting the recording session for acquisition of the EEG, the subject was asked to stay as calm as possible during the test. First, a scene containing the picture of an object was shown to the user. Then next, 5 slides containing several instance of the object in different locations in the scene was displayed. The subject was instructed to read the scene and identify the objects in the scene. During this process the

EEG of the subject was acquired and recorded. This experiment was conducted on different subject and on same scene. The process is depicted in the figure-5.2 below. The EEG acquired from the subject is plotted in Figure-5.3.

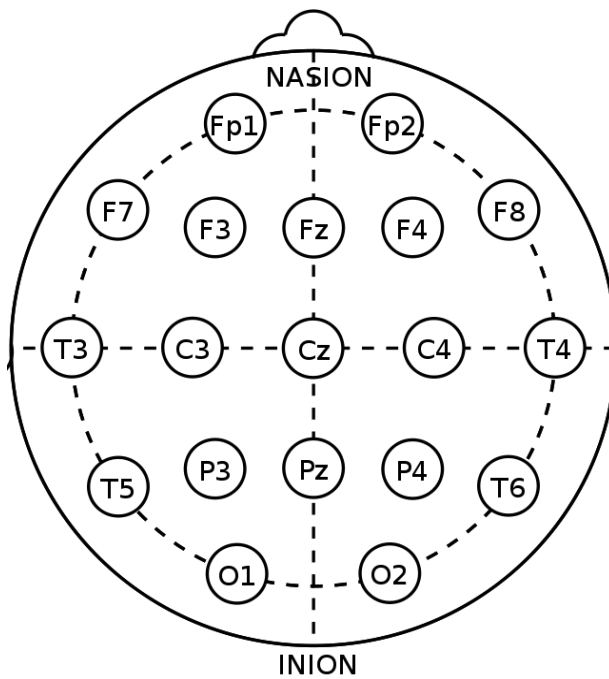


Fig 5.2

Fig 5. 2 Cross sectional view of 10-20 electrode placement diagram.



Figure 5.3

Fig 5. 3 Subject wearing EEG cap while recording of EEG and EOG signal

(Courtesy AxxonetPvt. Ltd., Bangalore, India)

The slides had images which were very basic. This was done in order get distinctive EEG signatures especially event related potentials. Some of the slides are given below and the respective task:

1. Fig 5 Shows the picture of a top view of an airport where there are planes of different sizes are present. The subject was asked to count the number of planes present.



Fig 5. 4 Slide to count the number of planes

2. Fig 6a shows the pic of a shape which the subject was ask to see carefully. In the next slide (Fig 6b) a pic containing different shapes was shown. The subject was asked to find and count the number of similar shapes.

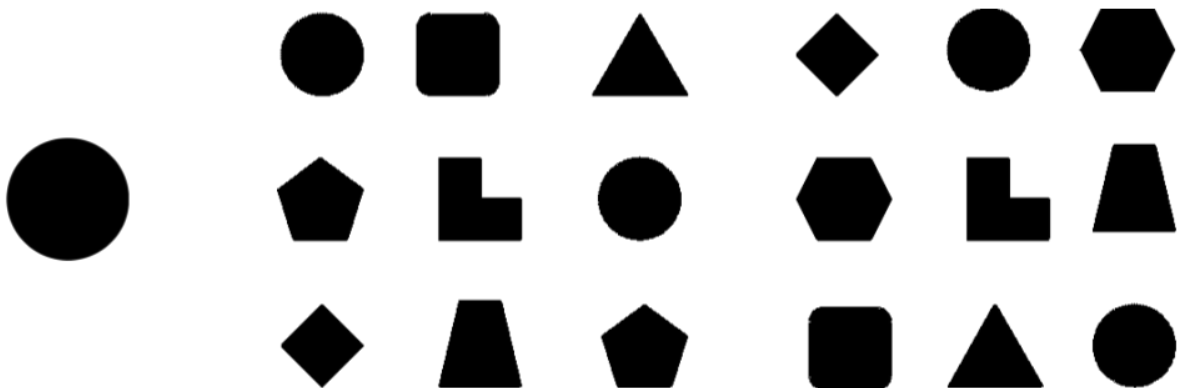


Fig 6a: Object

Fig 6b : objects shown out of which the user needs to find the target object.

3. Fig 5.5 given below was another unique slide which was shown to the subject and is asked to read the passage carefully and then find the number of time the word ‘defence’ and ‘development’ is written.

The Defence Research and Development Organisation (DRDO) is an agency of the Government of India, charged with the military's research and development, headquartered in New Delhi, India. It was formed in 1958 by the merger of the Technical Development Establishment and the Directorate of Technical Development and Production with the Defence Science Organisation. It is under the administrative control of the Ministry of Defence, Government of India.

With a network of 52 laboratories, which are engaged in developing defence technologies covering various fields, like aeronautics, armaments, electronics, land combat engineering,

Fig 5. 5 Passage shown to the subject

While recording the EEG the distance from the monitor to the subject is kept at a distance of 93cm. Monitor size is (30x60 cm²). The distance from the camera to subject is 27cm. The camera feed is used for gaze estimation and provide approximate coordinates of the eye-fix on the monitor screen.

5.7 Summary

EEG acquisition is a vital step in the process the whole experiment. The isolation of the noise is of high priority in order to get pure EEG signal. That way we would not need to apply the noise removal techniques in the first place. Subject selection and subject awareness plays the most important role while performing this experiment. Without proper precautionary measures there is every possibility of the signal being polluted.

References:

1. Maureen Clerc, Laurent Bougrain, Fabien Lotte “Brain–Computer Interfaces 2: Technology and Applications“ 30 August 2016, DOI:10.1002/9781119332428

Chapter 6: A Method to Detect Blink from the EEG Signal

6.1 Introduction

Electroencephalogram (EEG) is a measure of the electrical signals of the brain of a human being. It is a readily available test that provides the evidence of how the brain functions over time. Brain-computer interface (BCI) is collaboration between a brain and a device that enables EEG signals from the brain to control some external activity, such as control of a cursor or a prosthetic limb [1]. The interface enables a direct communications pathway between the brain and the object to be controlled. Electrooculography (EOG) is a technique for measuring the corneo-retinal standing potential that exists between the front and the back of the human eye. The resulting signal is called the electrooculogram. Tracking the movement of eye through sensors enables to compute and fix the position where one's eyes are focused [2]. Study of EOG can determine presence, attention, focus, drowsiness, consciousness or other mental states of the subject [3], [4], [5]. Event Related Potential (ERP) is a small voltage generated in brain due to the occurrence of a specific event or stimuli. ERPs can be reliably measured from EEG.

In this research we characterize the EEG signal and propose a method to detect and process the EOG signal. When active, i.e. not in the state of sleep the external functioning of human eye is characterized by three distinct functions viz. saccadic, fix and blink. Saccadic and fix are voluntary actions or actions controlled by human. Whereas the blink is an involuntary action which is associated with randomness and high fluctuation of EEG voltage [6]. We discuss how to capture the EEG and EOG signal and how to filter the EEG channel to delineate the EOG and

related signals from other channels. Then we discuss the process to characterize and delineate the blinks from the rest of the EEG signals so that saccadic and fix are delineated.

6.2 Process of EEG Data Acquisition

In our experiment, Axxonet's Brain Electro Scan System (BESS) which is a 32 channel EEG system, was used to record the EEG data of the subjects. The system has maximum sampling rate per channel of 30kps and runs on 5V AC supply. Gold plated silver electrodes soaked in saline water were used. The detection of Beta waves (16-31 Hz) which is responsible for cognitive actions like thinking, planning, focusing, high alert etc., is profoundly observed over the recorded data. Initially notch filter of 0.5 to 75 Hz was applied. T8, CP6, A1, A2 channels were used to record EOG data. 10-20 electrode placement system is used to record EEG data. Depicted below in Figure 6.1 and Figure 6.2 is the cross sectional view of the electrode placement to capture the EEG and one of the subject while capturing the EEG data respectively.

6.3 EOG Data Acquisition

Before starting the recording session for acquisition of the EEG, the subject was asked to stay as calm as possible during the test. First, a scene containing the picture of an object was shown to the user. Then next, 5 slides containing several instance of the object in different locations in the scene was displayed. The subject was instructed to read the scene and identify the objects in the scene. During this process the EEG of the subject was acquired and recorded. This experiment was conducted on different subject and on same scene. The process is depicted in the figure-6.3 below. The EEG acquired from the subject is plotted in Figure-6.4.

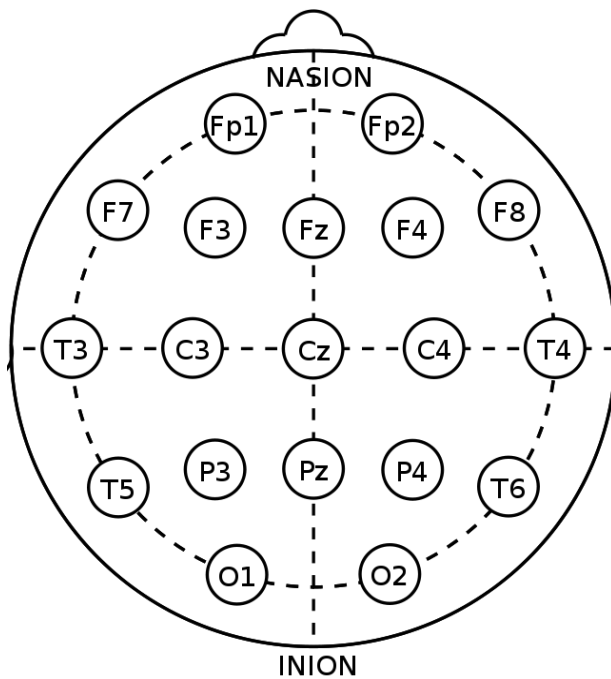


Figure 6.1



Figure 6.2

Fig 6. 1 Cross sectional view of 10-20 electrode placement diagram.

Fig 6. 2 Subject wearing EEG cap while recording of EEG and EOG signal

(Courtesy AxxonetPvt. Ltd., Bangalore, India)

While recording the EEG the distance from the monitor to the subject is kept at a distance of 93cm. Monitor size is (30x60 cm²). The distance from the camera to subject is 27cm. The camera feed is used for gaze estimation and provide approximate coordinates of the eye-fix on the monitor screen.



Fig 6. 3 EOG electrode placement on subject

6.4 Blink Detection

The EEG signal with highly varying voltage and frequency. Also the baseband of the signal varies frequently.

Blink in EEG & EOG signals are considered as artefacts in the EEG. To filter and detect the blink from the EEG we propose a novel technique of blink detection in the paper.

Step-1: EEG data acquired in. edf format is loaded in MATLAB using EEGLAB toolbox (version 14.1.2b).

Step-2: Plot the EEG acquired in step-1 to visualize the recorded data for all channels. Sampling rate was set to 1024 Hz.

Step-3: Our application was mostly concerned with frequencies in the range 0-30 Hz. We filtered the overall channel signals into 1-30 Hz frequency using Standard Filtering technique available in the EEGLAB Toolbox. After visual analysis of the plot obtained, it was found that the impact of the blinks was mostly affecting FP1, FP2, A1(EOG1),

A2(EOG2). Hence, this 4 channels are used for further processing of blink detection.

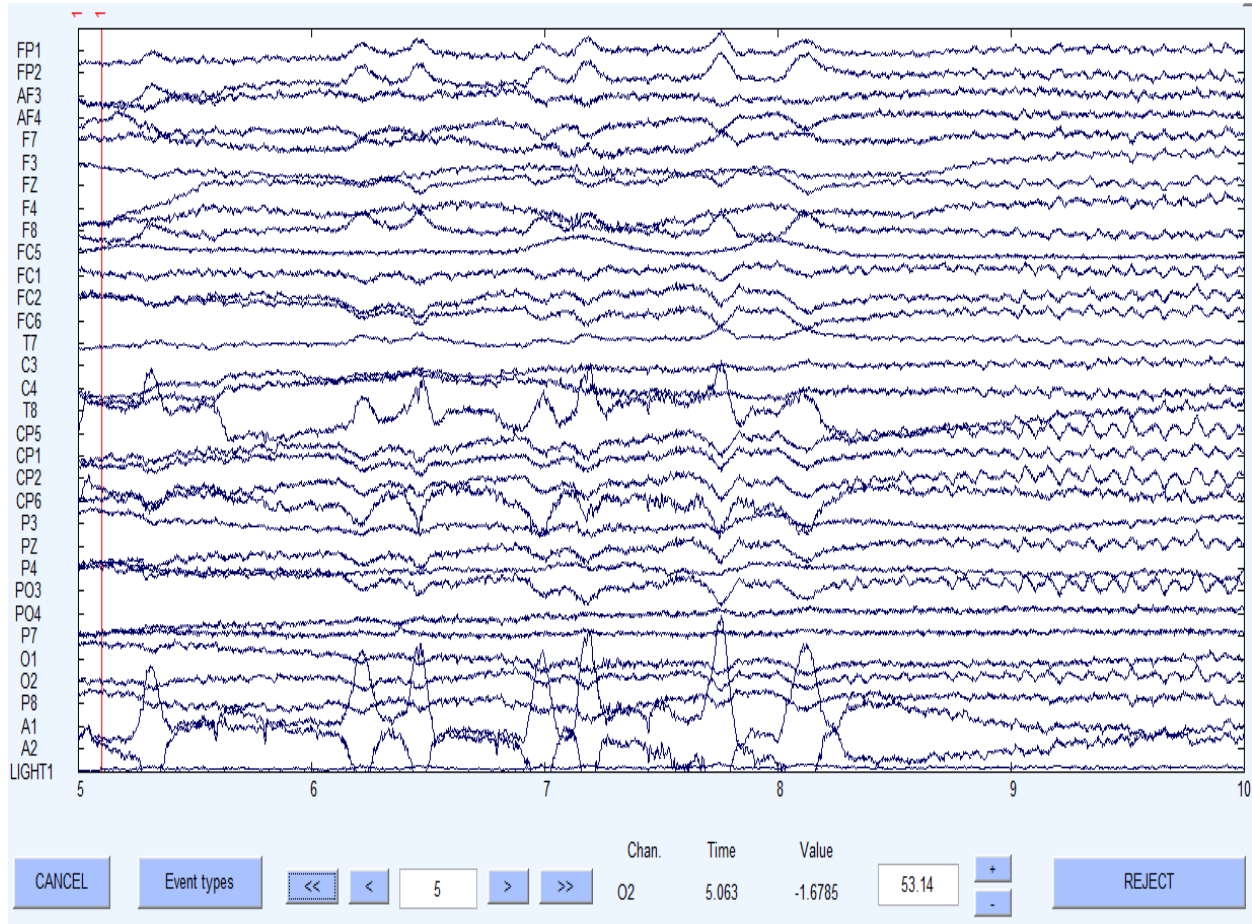


Fig 6. 4 32 Channel EEG data plot using EEGLAB Toolbox (Version 14.1.2b)

Step-4: After filtering, the signal contained too many fluctuations over very short time period. In order to get rid of unwanted fluctuations and make the signals smoother the signals were subjected to a moving average technique. Figure 6.5 illustrates the results obtained for two individual blink occurrence.

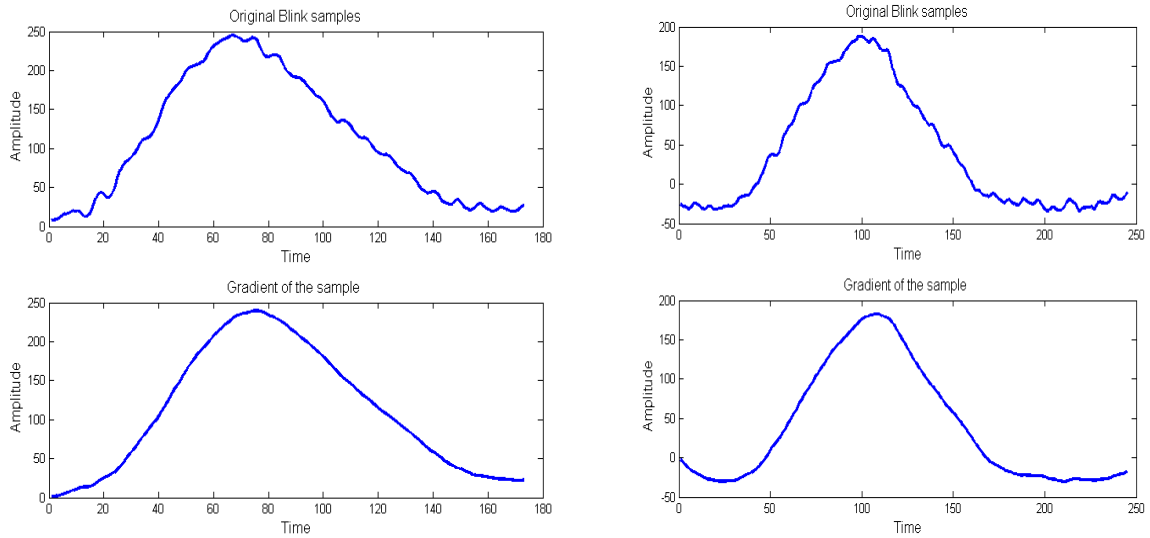


Fig 6. 5 Two blink samples and the resulting signal after applying Moving Average technique

As shown in Figure 6.6 the DC value for each individual blink sample is highly varying, therefore standard threshold technique will produce very poor results if applied. Thus calculation of Gradient for the signal will result in better detection of the activity of the peaks caused by blinks.

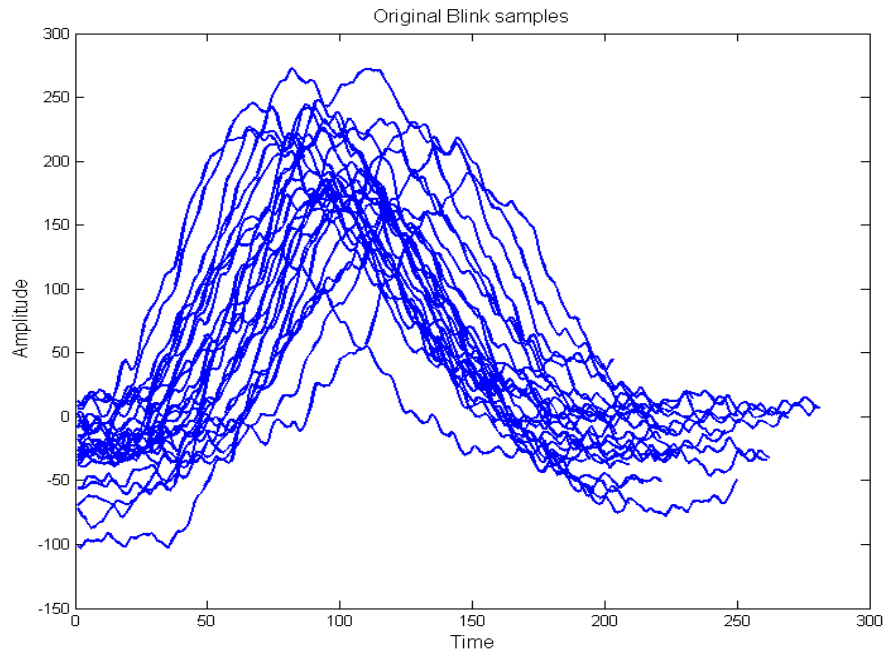


Fig 6. 6 Overlapped Plot of 29 blink samples

Step-5: Blinks were detected using following method:

- The signal from channel EOG1 was selected and Moving Average technique was applied on it with Lead parameter value 10 and Lag parameter value 20. The result is shown in Figure 6.7, first subplot.
- Gradient of the signal was obtained and shown in the second subplot.

Step-6: A modified threshold technique was applied on gradient to obtain the duration of each individual blinks. The threshold function is defined as below:

$$f(x) = \begin{cases} 2T, & x \geq T \\ T, & 0 \leq x < T \\ -T, & 0 > x > -T \\ -2T, & x \leq -T \end{cases}$$

Where,

$$T = C * \operatorname{argmax}(|x|)$$

$$C = 0.3$$

C is a constant that needs to be adjusted for proper blink detection generally in range (0.1 to 0.5)

Step-7: After applying the threshold function the resultant starting and ending points of the blink is highlighted on the original signal and shown in fourth subplot. Hence, this technique of blink detection was applied on the whole signal and for all selected channels.

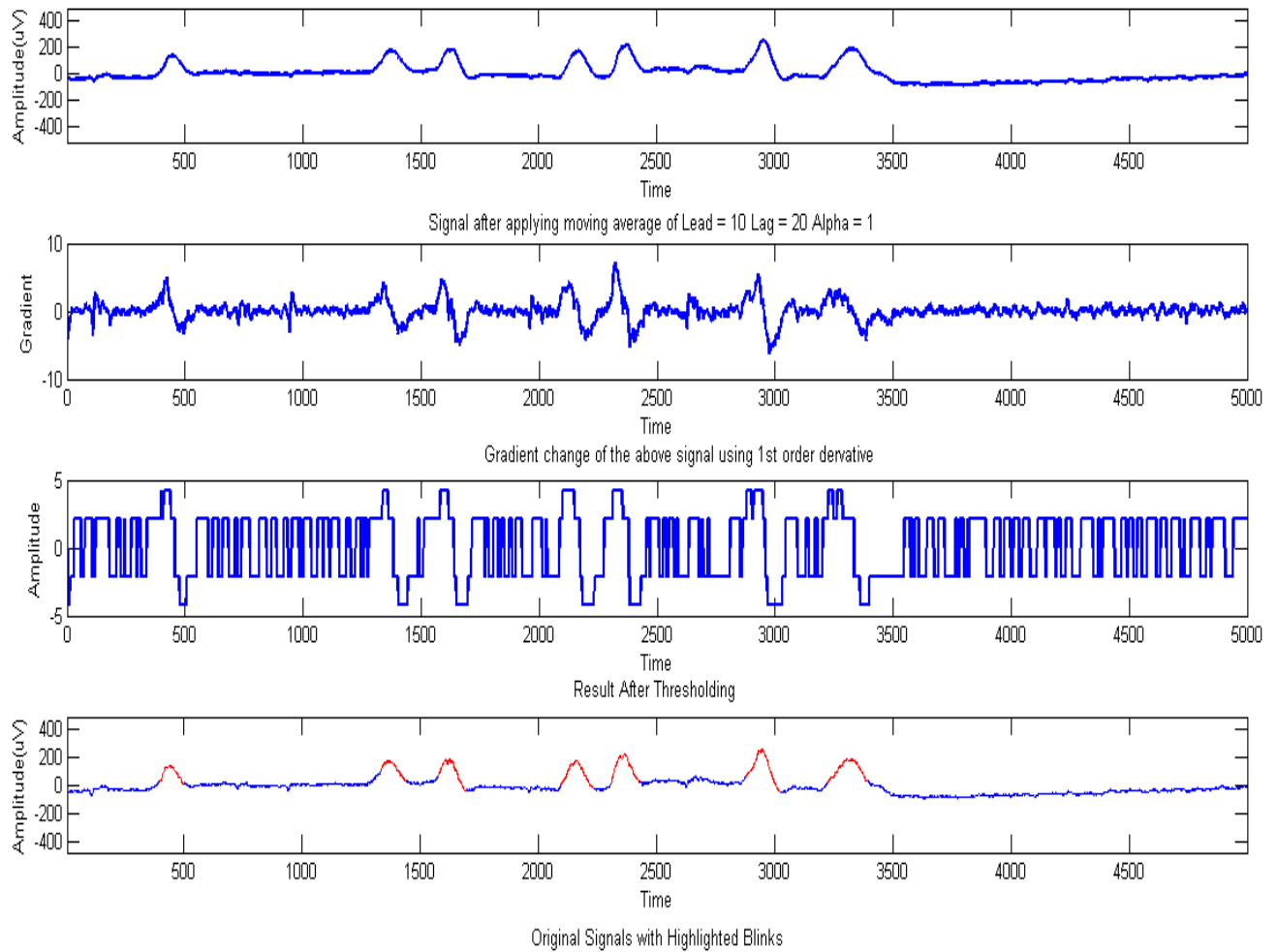


Fig 6. 7 Detection of blinks in EEG data stream

6.5 Results

The algorithm was tested on 2 subjects' recordings and the corresponding results are shown in Table 1.

Subject	Data Point Range (x1000)	C	Lag	Lead	No of Blinks Present	True Positives	False Negatives	Accuracy (%)
1	5-30	0.3	5	10	11	8	0	65.38
	30-60	0.3	5	10	14	8	0	
	60-90	0.3	5	10	31	19	1	
	90-120	0.3	5	10	25	14	1	
	120-160	0.3	5	10	27	23	2	
	160-180	0.3	5	10	13	9	0	
	180-198.656	0.3	5	10	9	4	2	
2	5-35	0.2	5	10	6	5	1	90
	35-65	0.3	5	10	1	1	0	
	65-95	0.3	5	10	1	1	0	
	95-125	0.3	5	10	-	-	-	
	125-185	0.3	5	10	1	1	0	
	185-204.8	0.3	5	10	1	1	0	

Table 6. 1 Algorithm accuracy for 2 subjects' EEG data

Due to the lengthy size of the data we divided the data in a range of 30,000 data points (29.3 sec as sampling rate is 1024 hz) and analysed them one by one. The constant C was adjusted for each data point range but it observed to be the same throughout the course of the experiment. Similarly, the Lag and the Lead for the moving average applied on the signal was also found to be same. These parameters were found to be the best for detection. To high values of Lead and Lag led to omission of the blinks and too low values of the Lead and Lag led to noisy blink signatures.

Taking subject 1 into consideration it was observed that subject 1 blinked frequently during the course of the experiment. A total of 130 blink were recorded manually out of which 85 were correctly detected

which gives an accuracy of 65%. The subject was tired while performing this experiment with signs of drowsiness. Consecutively such high blink rate was observed as it was difficult to concentrate on the task.

On the hand Subject 1 was well rested and relaxed and throughout the experiment a total of 10 blinks were recorded manually out of which 9 were detected successfully. Thus the detection accuracy was 90%. Subject 1 and 2 were given the same set of task to perform. As the subject 2 was well rested it can be concluded easily that the subject performed the task with a very low blink rate as the concentration level was high.

6.6 Applications

Applications of blink detect are many. One of them being determination of one's concentration level and drowsiness. It was found out according to the latest research ^[10] that the mean blink rate at rest was 17 blinks per min and during conversation it increased to 26 and it was as low as 4.5 while reading. Based on the statistics we can infer that a subject's concentration level is high if it has a blink rate of at most 6 per min. Otherwise the subject is either low in his concentration level or distracted. However, if it is observed that the blink duration of the subject is above a certain level, then the subject is feeling drowsy. Blink is considered as an artefact during EEG analysis. Therefore, detection of blinks is used to remove them from original signal for further analysis.

6.7 Summary

The methodology used in the experiment includes gradient calculation and a modified threshold function to detect the blinks in EEG signal. As a result, this method for detecting blinks is computationally cost

effective compared to other traditional methods [7], [8], [9]. Blinks can also be used to measure alertness, drowsiness and other cognitive states. Future research can be extended towards detection of different mind states by using the blink detection technique. Further pattern recognition techniques using Deep Neural Network with multiclass classifier can be implemented to recognize cognitive states.

References:

1. Roy, Rinku&Konar, Amit &Tibarewala, D.N.. (2011). Control of artificial limb using EEG and EMG - a review.
2. N. Panigrahi, K. Lavu, S. K. Gorijala, P. Corcoran and S. P. Mohanty, "A Method for Localizing the Eye Pupil for Point-of-Gaze Estimation," in *IEEE Potentials*, vol. 38, no. 1, pp. 37-42, Jan.-Feb. 2019. doi: 10.1109/MPOT.2018.2850540 keywords: {Eyes;Gazetracking;Videos;Digital images},
URL: <http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8595416&isnumber=8595411>
3. TejeroGimeno, Pilar& Pastor, Gemma &Choliz, Mariano. (2006). On the concept and measurement of driver drowsiness, fatigue and inattention: Implications for countermeasures. *Int. J. of Vehicle Design*. 42. 67 - 86. 10.1504/IJVD.2006.010178.
4. Liu, Ning-Han & Chiang, Cheng-Yu & Chu, Hsuan-Chin. (2013). Recognizing the Degree of Human Attention Using EEG Signals from Mobile Sensors. *Sensors (Basel, Switzerland)*. 13. 10273-86. 10.3390/s130810273.
5. Lin, Chin-Teng, et al. "EEG-based drowsiness estimation for safety driving using independent component analysis." *IEEE Transactions on Circuits and Systems I: Regular Papers* 52.12 (2005): 2726-2738.
6. Different Effects of Voluntary and Involuntary Attention on EEG Activity in the Gamma Band
Ayelet N. Landau, Michael Esterman, Lynn C. Robertson, ShlomoBentin, and William Prinzmetal.
7. Sawant, Hemant K., and Zahra Jalali. "Detection and classification of EEG waves." *Oriental Journal of Computer Science and Technology* 3.1 (2010): 207-213.
8. Amin HafeezUllah, MumtazWajid, Subhani Ahmad Rauf, Saad Mohamad Naufal Mohamad, Malik Aamir
Saeed. Classification of EEG Signals Based on Pattern Recognition Approach. *Frontiers in Computational Neuroscience* 2017. DOI=10.3389/fncom.2017.00103. 1662-5188
9. Lotte, Fabien, et al. "A review of classification algorithms for EEG-based brain-computer interfaces." *Journal of neural engineering* 4.2 (2007): R1. <https://doi.org/10.1088/1741-2560/4/2/R01>
10. Bentivoglio AR¹, Bressman SB, Cassetta E, Carretta D, Tonali P, Albanese A. "Analysis of blink rate patterns in normal subjects." 1997 Nov;12(6):1028-34. DOI:[10.1002/mds.870120629](https://doi.org/10.1002/mds.870120629)

Chapter 7: *Saccade & Fix Detection from EOG signal*

7.1 Introduction

The physical activities of human eye constitute of three repetitive activities, viz saccade, fix and blink. Blink being an involuntary action, the saccades and fix correspond to different cognitive actions of human being. Often these actions are guided with active correlation of actions of neurological activities of the brain. A saccade is defined by the movement of the eyeball from one viewpoint to another. A saccade action can be captured through the EOG signal which is characterized by sudden deflection of the voltage fluctuation in the EOG. Study and analysis of saccadic movement and its pattern has many applications which can lead to understanding of cognitive capabilities of human beings.

Advancement of EEG acquisition system and development of sophisticated computing methods to process EOG signal has led to its widespread applications. Artifacts of EEG signals are being used to control IOT devices, to compute cognitive capabilities and agility of the mind, to forecast any epileptic activity, etc.

In this paper we propose a method to compute and delineate the EEG signal. We apply Wavelet decomposition transform followed with median filter to segregate the EEG signal corresponding to the saccadic movement. In this process first we apply the wavelet denoising transform [1] to remove the local fluctuations from the signal. Then CWT applied to find the coefficients required to detect the saccades and eventually the fixes.

Finally, we design a function which uses positive and negative threshold to detect the saccadic movements in the signal. It is observed that fixations are interleaved b/w two saccades of the eye[2,3]. This

process of saccade detection in the EOG signal is performed after removing the baseline DC value. This process is depicted in the block diagram given in the figure.

7.2 Methods

7.2.1 Block Diagram

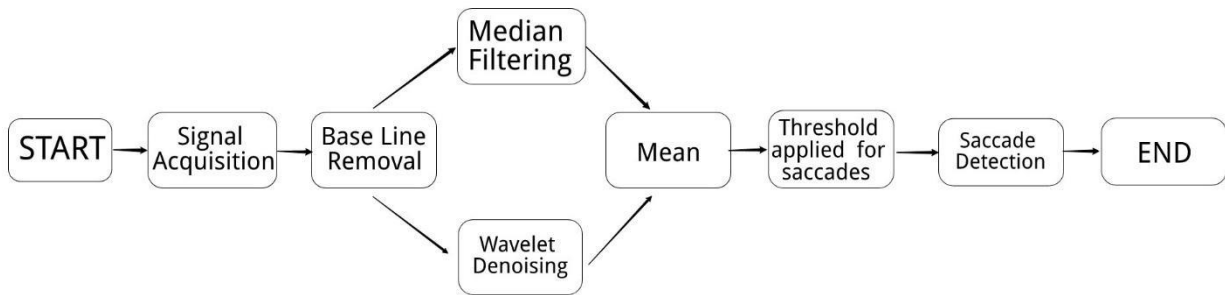


Table 7. 1 Block Diagram for Saccade Detection System

7.2.2 Baseline Drift Removal

Baseline drift is the short time variation of the baseline from a straight line caused by electric signal fluctuations. Baseline drift can occur due to breathing, loose contact between electrode and skin or body movement. It compromises the information content in the signal. In order to remove this, we performed multilevel 1D wavelet decomposition at level 12 using a reverse bi-orthogonal wavelet "rbio6.8" [4]. Reverse bi-orthogonal wavelets are obtained by bi-orthogonal wavelet pairs which exhibits linear properties which is advantageous for our experiment.

Figure 7.1 represents the comparison between original signal and signal after baseline drift removal. Baseline drift removal results in proper analysis of the signal as described above. As discussed in chapter 3, the sources of baseline wander maybe different, but it always appears

as a low-frequency artifact that introduces slow oscillations in the recorded signal.

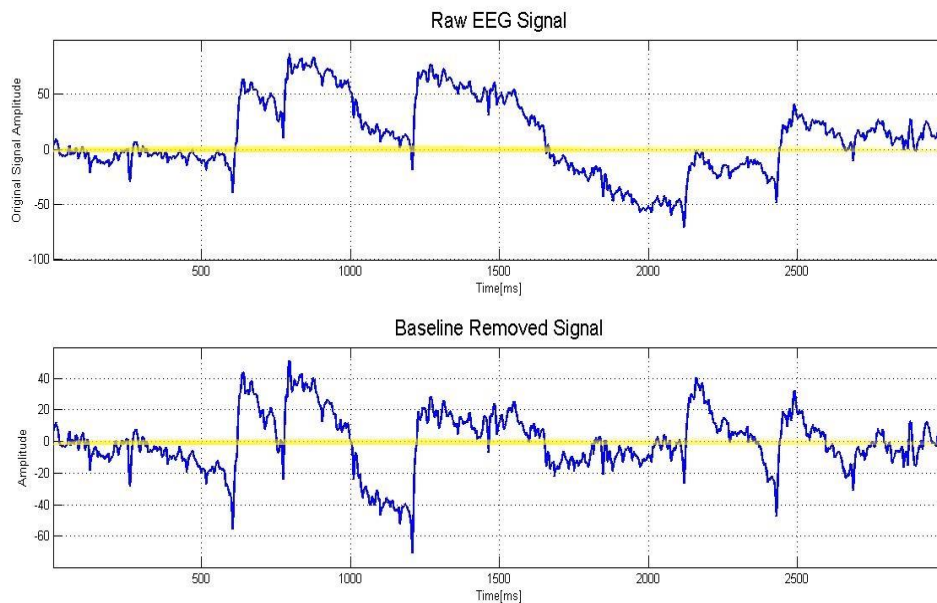


Fig 7. 1 Comparison of the original signal and baseline removed signal

7.2.3 Noise Removal

We observed that the information contained in the EOG signal had noise, which affected the process of detection of the saccades. This was due to the bad placement of the electrodes, muscle twitches, random head movements and local electrical interferences. The removal of this noise required careful selection of the filtering technique to be applied. Based on our research, median filtering and wavelet denoising appeared to be best suited for our problem.

7.2.4 Median Filtering

Median filtering is a window based noise removal technique where the window takes the median of its values and replaces them with it. For our problem it was particularly helpful as it preserved the steep nature of the saccades. However, the window size of the median filter was a matter of concern as large windows distorted the edge and shape of the saccades

and also possibly removed the small saccades. As a result, it was a trade-off between precision vs noise.

For our application the order of the filter was varied between 10 and 40 and it was visually observed and concluded that the best possible parameter was a median filter of 19 order and window size of 74 ms. This filter not only prevented the removal of small saccades of interests but also successfully removed the noise that was present. Figure 7.2 describes the comparison of the process.

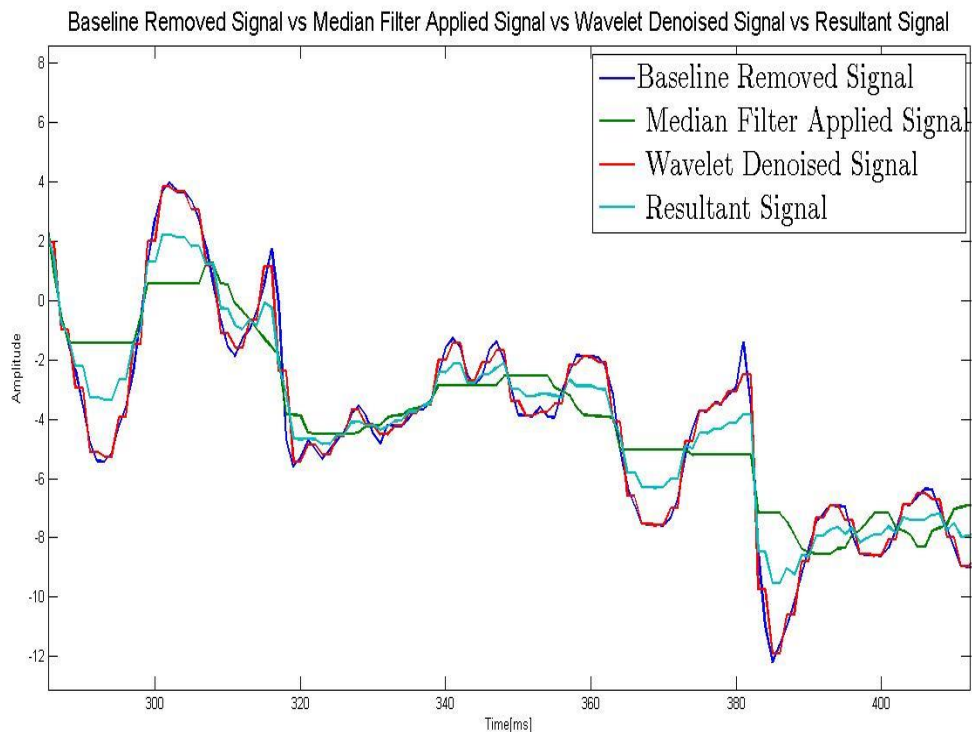


Fig 7. 2 Illustration of filtering techniques applied on the signal

7.2.5 Wavelet Denoising

Wavelet denoising is a noise removal technique where the mother wavelet is passed through the signal and the correlation coefficients are obtained [5]. After that a soft/hard thresholding is applied, removes the low amplitude noise from the signal.

For our application the inbuilt MATLAB function “wden” was used to perform the denoising. The signal was denoised using “Symlet” wavelet of level 1 and soft thresholding was applied on the coefficients with universal threshold $th = \sqrt{\ln \ln N}$, where N is the length of the time series.

The results of the noise removal obtained independently were taken and was averaged out and the resulting signal obtained was devoid of noise of higher frequency.

7.2.6 Saccade Detection

Saccades are observed as abrupt change in voltage (similar to step functions). Continuous Wavelet Transform (CWT) [6, 7] is very sensitive to this kind of change. We applied ‘Haar’ mother wavelet with a scale of 20 at level 12 to the signal after baseline removal and denoising [8]. ‘Haar’ wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet. Therefore, due to similarity with saccade’s shape ‘Haar’ wavelet was chosen to carry on the experiment.

A threshold of ± 25 was applied on the resulting CWT coefficients. Positive and negative peaks above the thresholds were marked which represents the occurrence of the saccades. Corresponding points were also marked in the original signal and the result is given in figure 7.3.

7.2.7 Fixation

A subject maintaining constant visual gaze on any particular location is known as fixation. The term "fixation" can either be used to refer to the point in time and space of focus or the act of fixating. Gaze points show what the eyes are looking at. If a series of gaze points is very close – in time and / or space – this gaze cluster constitutes a fixation, denoting a period where the eyes are locked towards an object. In our experiment

the subject was asked to concentrate on the Image in front and therefore we can conclude that in between two saccades there is a fix. After detection of saccades the time interval between two saccades are marked as fix as show in figure 7.4.

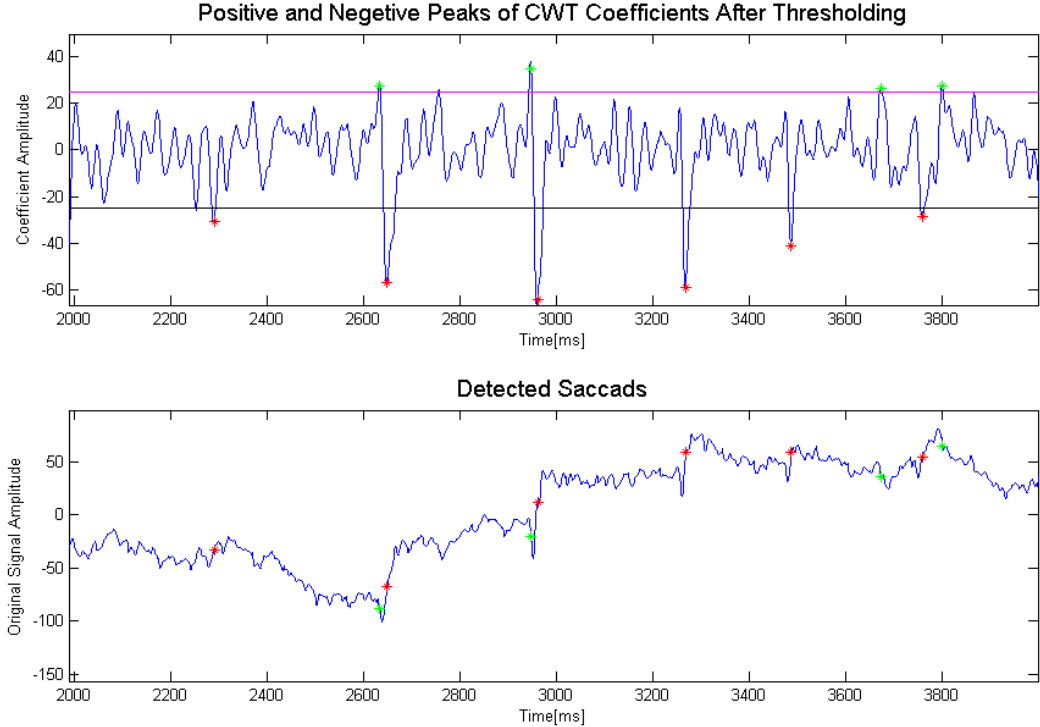


Fig 7. 3 CWT coefficients of the signal with a threshold ± 25 (top) and Corresponding Saccades (bottom)

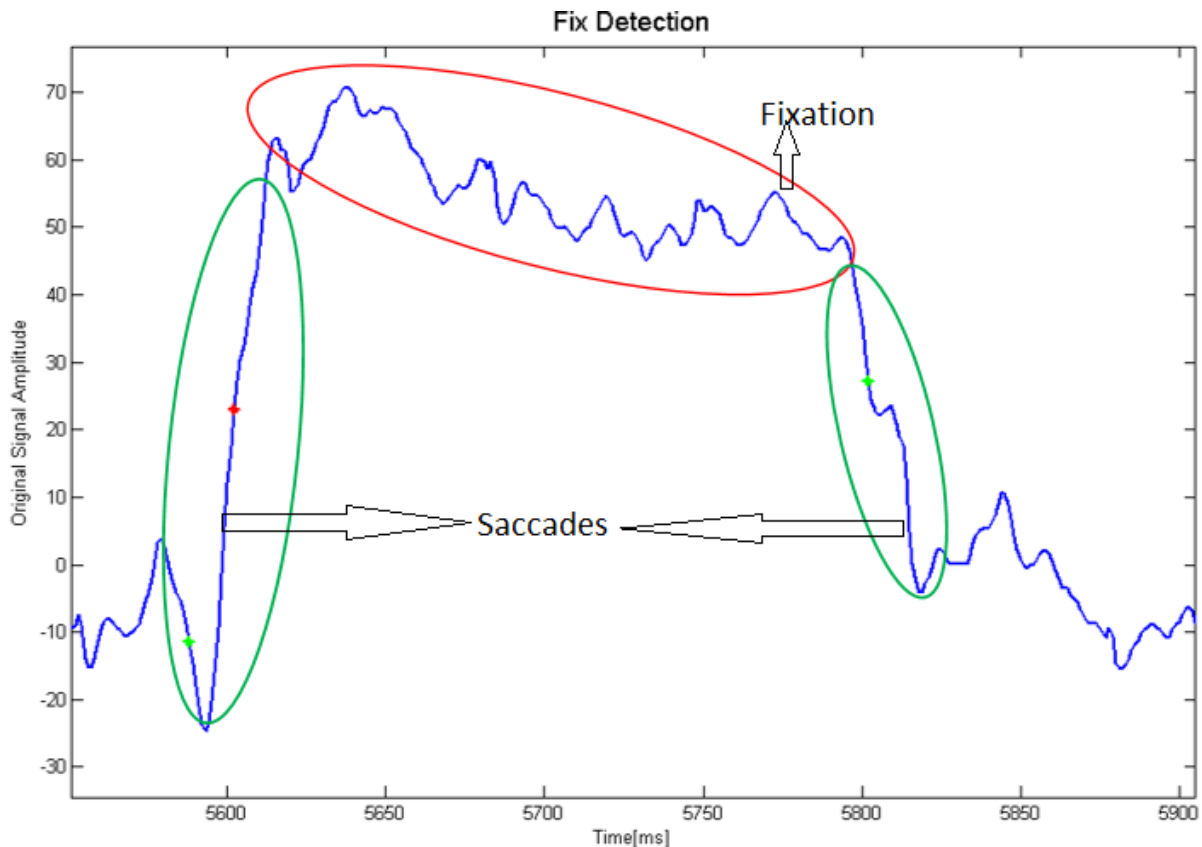


Fig 7. 4 Demonstration of fix and saccades

7.3 Summary

In this experiment saccades and fixes were successfully segregated after applying appropriate noise removal and baseline drift removal techniques. Our future work proposal is to determine direction of the eye movement using detected saccades and plot a graph for further analysis. With the detected fixes we also propose to detect the presence of P300 event related potentials. This will relate to whether the subject is looking at an object of interest or not.

References:

1. P. B. Patil and M. S. Chavan, "A wavelet based method for denoising of biomedical signal," *International Conference on Pattern Recognition, Informatics and Medical Engineering (PRIME-2012)*, Salem, Tamilnadu, 2012, pp. 278-283.
doi: 10.1109/ICPRIME.2012.6208358
2. Henderson John M. and Hollingworth Andrew, "Eye movements and visual memory: Detecting changes to saccade targets in scenes", *Perception & Psychophysics (2003)* 65: 58.
doi="10.3758/BF03194783"
3. Henn V and Cohen B, "Quantitative analysis of activity in eye muscle moto neurons during saccadic eye movements and positions of fixation", *Journal of Neurophysiology (1973)*,
doi = {10.1152/jn.1973.36.1.115}
4. S. Gupta and H. Singh, "Preprocessing EEG signals for direct human-system interface," *Proceedings IEEE International Joint Symposia on Intelligence and Systems*, Rockville, MD, USA, 1996, pp. 32-37.
doi: 10.1109/IJSIS.1996.565048
5. J. Gao, H. Sultan, J. Hu and W. Tung, "Denoising Nonlinear Time Series by Adaptive Filtering and Wavelet Shrinkage: A Comparison," in *IEEE Signal Processing Letters*, vol. 17, no. 3, pp. 237-240, March 2010.
doi: 10.1109/LSP.2009.2037773
6. Pan Du, Warren A. Kibbe, Simon M. Lin, Improved peak detection in mass spectrum by incorporating continuous wavelet transform-based pattern matching, *Bioinformatics*, Volume 22, Issue 17, 1 September 2006, Pages 2059–2065, <https://doi.org/10.1093/bioinformatics/btl355>
7. Z. Nenadic and J. W. Burdick, "Spike detection using the continuous wavelet transform," in *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 1, pp. 74-87, Jan. 2005.
doi: 10.1109/TBME.2004.839800
8. A. Bulling, J. A. Ward, H. Gellersen and G. Troster, "Eye Movement Analysis for Activity Recognition Using Electrooculography," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 4, pp. 741-753, April 2011. doi: 10.1109/TPAMI.2010.86

Chapter 8: *Conclusion & Future Scope of Work*

8.1 Conclusion

In this thesis we addressed to the problem of detecting EEG artifact Blink and EEG characteristics Saccade and Fixation. One of the main contributions of our work is to express this task as a combinatorial optimization problem with constraints, and to propose methods to solve it. Including multiple parameter gives the algorithms to perform better while adjusting them for deviating scenarios.

A discussion on different preprocessing, processing and classification techniques for EEG signal are provided. The selected methods among them are chosen to be best fit for the problem in hand. In particular, we used methods which are suitable for resulting in maximum true positives and minimum false positives.

The main focus of the thesis is to identify saccadic movements and segregate fixations. This leads to the problem of detection and dissociation of blink artefacts in first stage. The problem with blink is it has highly fluctuating DC offset value. Therefore, applying threshold to EEG signal will not result in good detection of blinks. The plot addressing this problem is duly discussed in blink detection chapter. The solution was to take the gradient of the signal and apply thresholding on it. The results improved significantly, and can be observed in the infogram provided.

After eliminating the blinks in order to detect saccades next approach is Continuous Wavelet Transformation (CWT). Denosing the signal is very crucial. For the need of application, we need to find a way to denoise the signal without hampering certain fluctuations (saccades) in the signal. The average of wavelet denoising and median filter serves the purpose perfectly.

Finally, another contribution relies in choosing the correct wavelet for detecting saccades. Along the various wavelets ‘Harr’ wavelet was best suited for the purpose of saccade detection as it is very responsive to certain change in voltage along the signal. In wavelet denoising ‘rbio-6.8’ is found to produce best results. These experiments were performed on multiple subjects’ data, where same task was provided to each of the subjects. The algorithm was also tested on readily available EEG data found over the internet. In both cases results show that our approach obtains better results and that converge to a solution by having to evaluate less individuals than other more usual evolutionary computation methods. These differences in the results have been proved to be statistically significant.

8.2 Future Scope of Work

Many different adaptations, tests, and experiments have been left for the future due to lack of time. Future work concerns deeper analysis of particular mechanisms, new proposals to try different methods. The following ideas could be tested-

8.2.1 P300 Analysis

The successful detection of saccades and segregation of fixations lead to run P300 analysis on the fixation points. P300 is an Event Related Potential (ERP) which gets generated after visual recognition of predefined objects. If a true P300 is found in a fixation it can be declared that the subject is looking at a certain object in an image/ map and vice-versa. Considering this we can justify a subject’s cognitive capability for image/map reading which can be a very useful military application.

8.2.2 Saccade Fix Graph

Map reading and understanding is an important skill of a human being. Reading and understanding the situation depicted by a map helps in locating spatial objects in terrain, navigation to the desired destination and appreciation of the general terrain under consideration. Map Reading Capability (MRC) of human being can be computed from the way the person reads the map. Also how the person reads the map in different scales. In order to understand the approach of the map reader the way he/she reads the map has to be studied. The approach of studying situation or a map by a reader is best captured through the opto-electric moment of the eye. This can be captured as the saccadic moments on fixes by the eye.

The idea is to capture saccadic and fixes while reading the map through a graph structure coined as saccadic-fix graph (SFG). The map reader is exposed to maps at various scale such as 1:50K, 1:100K and 1:150K etc. Keeping the display layout are instantaneous field of the reader fixed with a fixed display and with the head fixed of the reader. The reader is asked to read a particular terrain object or objects appearing in the map. The ocular movement of the map reader is captured as SFG. The SFG further studied to compute the MRC of the map reader.

Therefore, the input to the system it maps are various scales with the IFOV of the reader fixed and the head fixed. The processing is to capture the electroocular movement of the map reader in the form of its saccadic and fixes for a predefined period of time. The output of the system should be SFG at different scale

8.2.3 Eye Gaze direction prediction

Eye gaze direction can be predicted using EOG data. As shown in Fig 1. A, B, C, D are four electrode placed for receiving EOG signal.

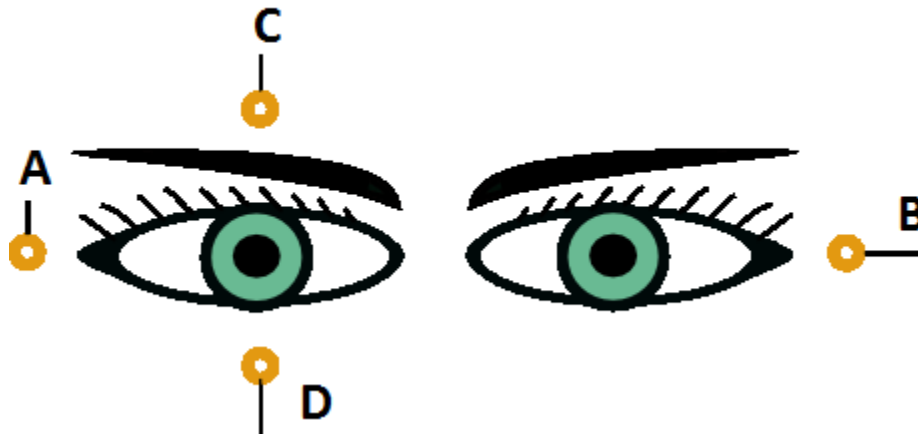


Fig 8. 1 Electrode placement for EOG recording

Now consider we encode the received data from each electrode in binary classes as shown below-



Lets consider direction of eye movement as below-

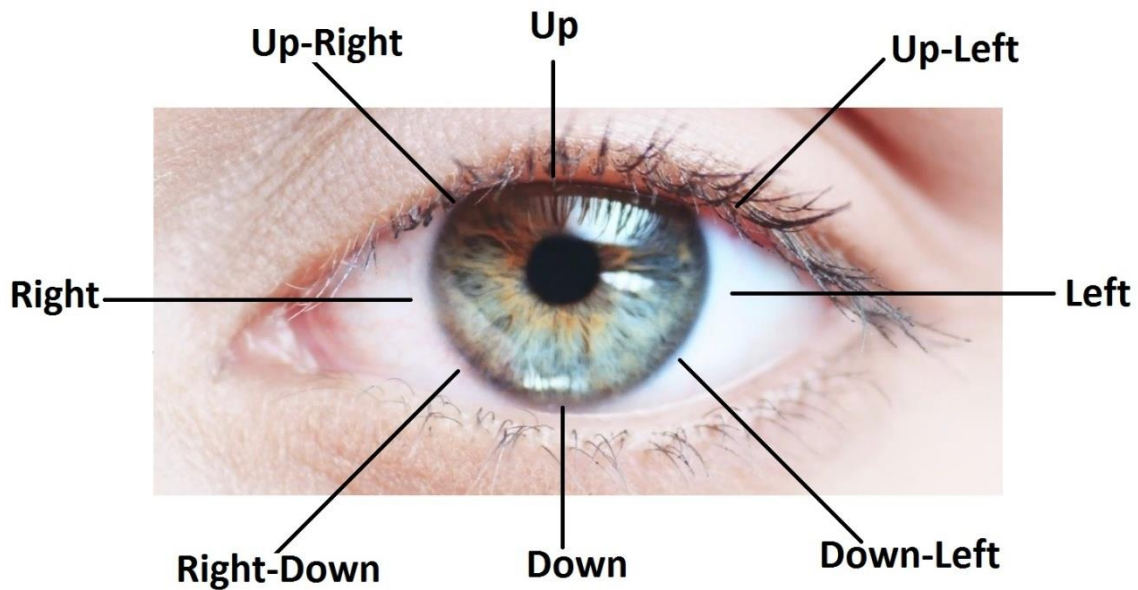


Fig 8. 2 Eye gaze directions

Now considering the encoded value of the electrodes following table can be used to predict eye gaze direction.

A	B	C	D	Direction of Gaze
1	-1	0	0	Right
1	-1	1	-1	Up-Right
0	0	1	-1	Up
-1	1	1	-1	Up-Left
-1	1	0	0	Left
-1	1	-1	1	Down-Left
0	0	-1	1	Down
1	-1	-1	1	Right-Down

Table 8. 1 Eye-Movement direction table with electrode encoder

8.2.4 Blink Application

Blink rate and blink duration can be used as measure of drowsiness and consciousness recognition system. Which is very effective for applications like driver/ pilot assistance. Blink is largely considered as artefacts in lot of EEG related studies. Therefore, detection of blinks can also be implemented as an artefact removal technique. In some EEG based IOT system periodic blink can be used as a gesture for certain functionality in the system.

Appendix

Loading the Data with EEGLAB Toolbox

To load the data in .edf format to matlab we have used EEGLAB toolbox. The source for the toolbox is provided in Software Requirement section. Step for loading data is as described below-

Step 1: Change current directory to eeglab folder. Add this path and in Matlab terminal type: "EEGLAB".

Step 2: A pop window will appear, now follow the path: "File >> Import data >> Using EEGLAB functions and plugins >> From EDF/EDF+/GDF files(Biosig toolbox)".

Now locate the edf file in file explorer and click open to import. Fig 1. Demonstrates the above path.

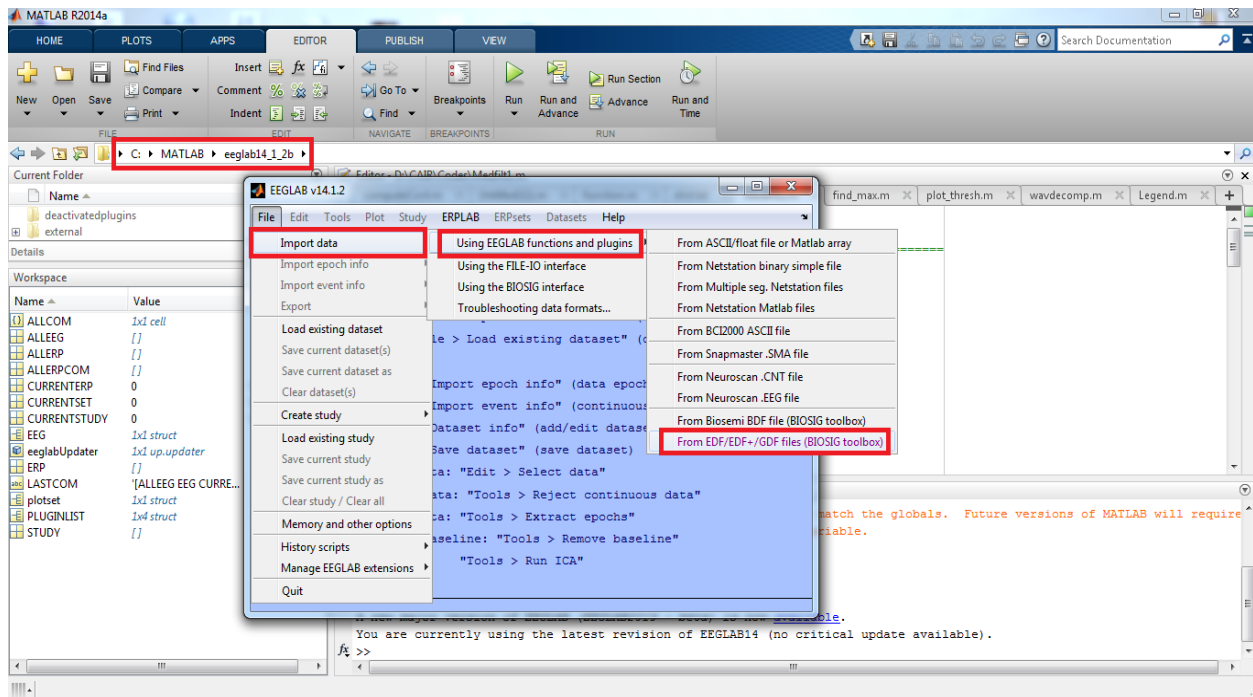


Fig 1. Loading .edf data in matlab using EEGLAB Toolbox

Step 3: After the import is complete to load the data as a mat file

for using in matlab type:

“A= ALLEEG.data;”

This stores the data in A (as matlab array) and let the user to access each channel by slicing the array. For our case it was 37 channel data, where each row in array represents one channel data. Note the data is in single format, so double conversion is required. Fig 2 demonstrates this process.

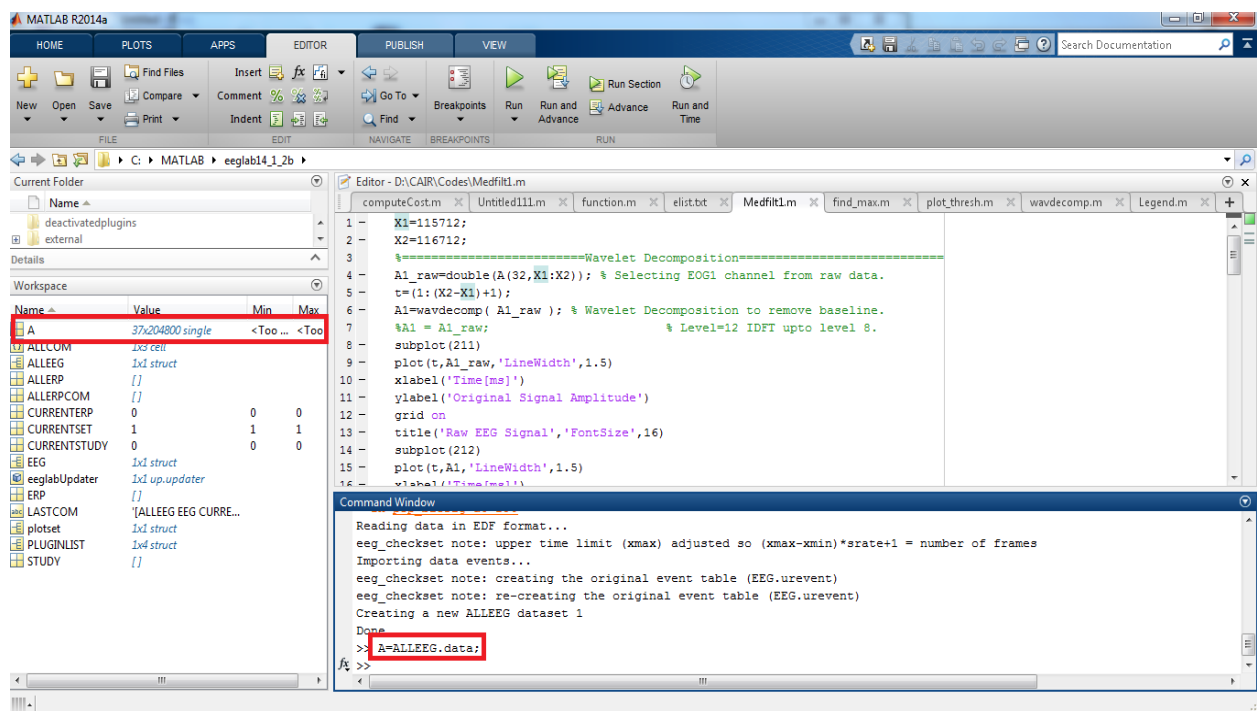


Fig 2. Converting the .edf file in Matlab Array

Blink Detection Matlab Code

Main Function

```
%{
=====
Title:A Method to Detect Blink from the EEG Signal
Author: Narayan Panigrahi, Center for AI and Robotics(CAIR), Bangalore,
        India, email: npanigrahi7@gmail.com
Amarnath De, student, Jadavpur University,
        amarnathde1992work@gmail.com
Somnath Roy, student, Jadavpur University, somroymail@gmail.com
=====
%}
%%
%EEG Signal aquired using EEGLAB Toolbox v14.1.2b
%A1 channel No 31 is taken for blink detection
channel1 = sangeeta(31,:);
t = 1:size(channel1,2);
%Moving average taken with Lead = 10 , Lag = 20, alpha = 1
%This is done to remove the local variations in the signal
[modified_long,modified_short] = movavg(channel1,10,20,1);
%%
%Takeing the differential of the signal to obtain the gradient
steps = 1;
grad = zeros(int32(size(modified_short,2)/steps));
fori = 1:(size(modified_short,1))/steps-1

        grad(i) = (modified_short(i+steps) - modified_short(i))/steps;

end
%%
%Calculating the parameters of the Modified threshold function
mod_val = abs(grad);
max_mod = max(mod_val);
c = 0.3;
thresh = max_mod*c;
%apply moving average using the same parameters
[ None ,smooth_grad] = movavg(grad,10,20,1) ;
%calling the Threshold function
[squared ,blinks,count_blinks] = thresh_sign(transpose(smooth_grad),...
        -thresh,thresh);

%Function to highlight the blinks in the original signal
plot_blinks(blinks,count_blinks , channel1)
%%
%plot the result
subplot(4,1,1)
grid on
plot(modified_short, 'LineWidth',1.5)
title('Signal after applying moving average of Lead = 10 Lag = 20Alpha= 1')
xlabel('Time')
ylabel('Amplitude(uV)')
subplot(4,1,2)
plot(grad,'LineWidth',1.5)
title('Gradient change of the above signal using 1st order dervative')
xlabel('Time')
ylabel('Gradient')
```

```

subplot(4,1,3)
plot(squared,'LineWidth',1.5)
title('Result After Thresholding ')
xlabel('Time')
ylabel('Amplitude')

```

Threshold Function:

```

%{
=====
Title:A Method to Detect Blink from the EEG Signal
Author: Narayan Panigrahi, Center for AI and Robotics(CAIR), Bangalore,
       India, email: npanigrahi7@gmail.com
Amarnath De, student, Jadavpur University,
       amarnathde1992work@gmail.com
Somnath Roy, student, Jadavpur University,
       somroymail@gmail.com
=====
%}
function [ y , blinks ,count_blinks] = thresh_sign( x , lower_thresh ,...
high_thresh)
%thresh_sign: This function determines the blinks.
%This function determines the blink if the the gradient crosses the higher
%and lower threshold in quick successions otherwise it won't.
%Input:gradient signal , lower threshold and higher threshold
%Output: squared signal, array containing the start and end of blinks
%and number of blinks

y = zeros(size(x));
plot(x)
pause
start=0;
ending=0;
flag = 0;
blinks = zeros(2,1);
count_blinks = 1;
fori = 2:size(x,2)

if( x(i)>high_thresh)

       y(i) = 2*high_thresh;

if(x(i-1)<=high_thresh&& x(i-1)>0)
if(flag == 1) % not a blink so set flag to 0
       flag = 0;
elseif(flag==0)
       start = i-1; %record the time of blink start
       flag = 1; %set flag to signify the start of blink

end
end

elseif(x(i)<=high_thresh&& x(i)>0)

```

```

        y(i) = high_thresh;

elseif(x(i)<0 && x(i)>lower_thresh)

        y(i) = lower_thresh;

if(x(i-1)<=lower_thresh)

if(flag == 1)
        ending = i-1; %record the time of blink ends
        flag = 0; %set flag to signify the end of blink
        blinks(:,count_blinks) = [start;ending];

count_blinks = count_blinks+1;
end
end

elseif(x(i)<=lower_thresh)
        y(i) = 2*lower_thresh;
end
end
end

```

Plot Blink Function:

```

%{
=====
Title:A Method to Detect Blink from the EEG Signal
Author: Narayan Panigrahi, Center for AI and Robotics(CAIR), Bangalore,
India, email: npanigrahi7@gmail.com
Amarnath De, student, Jadavpur University, amarnathde1992work@gmail.com
Somnath Roy, student, Jadavpur University, somroymail@gmail.com
=====
%}
function [] = plot_blinks( blinks , count_blinks , channell)
%plot_blinks: Highlights the blinks in the original signal
count = 1;
start = blinks(1,1);
ending = blinks(2,1);
subplot(4,1,4)
for t = 2:size(channell,2)

if(t>=start && t <= ending)

        plot(t-1:t,channell(t-1:t), 'r', 'LineWidth',1.5)
        hold on

else

        plot(t-1:t,channell(t-1:t), 'LineWidth',1.5)
        hold on

end

if (t>ending && count<count_blinks-1)%if plot completes one blink

```

```
        count = count +1;
        start = blinks(1,count);
        ending = blinks(2,count);
end

end
title('Original Signals with Highlighted Blinks')
xlabel('Time')
ylabel('Amplitude(uV)')
```

Saccade and Fix Detection Matlab Code

Main Function:

```
X1=115712;
X2=116712;
%=====Wavelet Decomposition=====
A1_raw=double(A(32,X1:X2)); % Selecting EOG1 channel from raw data.
t=(1:(X2-X1)+1);
A1=wavdecomp( A1_raw ); % Wavelet Decomposition to remove baseline.
%A1 = A1_raw; % Level=12 IDFT upto level 8.
subplot(211)
plot(t,A1_raw,'LineWidth',1.5)
xlabel('Time[ms]')
ylabel('Original Signal Amplitude')
grid on
title('Raw EEG Signal','FontSize',16)
subplot(212)
plot(t,A1,'LineWidth',1.5)
xlabel('Time[ms]')
ylabel('Amplitude')
grid on
title('Baseline Removed Signal','FontSize',16) %Comparison Plot of baseline
%removed signal.

%=====Median Filter and Wavelet Denoising=====

A1_medfilt=medfilt1(A1,19,74); % Applying Median filter of 19th order with
% window of 74ms.

[A1_wden] = wden(A1,'sqtwolog','s','one',1,'sym1'); % Applying symlet
%wavelet denoising to remove noise
A1_final=(A1_medfilt+A1_wden)/2; % Averaging both to get final signal.

figure,plot(t,A1,t,A1_medfilt,t,A1_wden,t,A1_final,'LineWidth',1.5)
xlabel('Time[ms]')
ylabel('Amplitude')
title('Baseline Removed Signal vs Median Filter Applied Signal vs Wavelet
Denoised Signal vs Resultant Signal','FontSize',16)
legend('Baseline Removed Signal ',' Median Filter Applied Signal',...
' Wavelet Denoised Signal',' Resultant Signal','FontSize',18)

figure,plot(t,A1,t,A1_final,'LineWidth',2)
title('A1 vs A1_final','FontSize',14)
xlabel('Time[ms]')
ylabel('Amplitude')
legend('Baseline Removed Signal',' Median Filter Applied Signal')

%=====Continuous Wavlet Transform=====

subplot(211)
A1_cwt=cwt(A1_final,20,'haar'); % Continuos 'Haar' Wavelet Transform to
% find abrupt change in voltage
% (saccades and blinks)

plot(A1_cwt,'LineWidth',2)
title('Cwt Coefficients','FontSize',16)
```

```

xlabel('Time[ms]')
ylabel('Coefficients Amplitude')

subplot(212)
plot(t,A1_final,'LineWidth',2)
title('Resulting Signal','FontSize',16)
xlabel('Time[ms]')
ylabel('Amplitude')

%=====saccad Detection=====
threshold = 25;
[start_pos ,ending_pos, start_neg, ending_neg ] = plot_thresh(A1_cwt,...
    A1_final,threshold); %Applying threshold on A_cwt to find abrupt changes
in
    %the signal
pos_points = [start_pos ; ending_pos];
neg_points = [start_neg ; ending_neg];
%max peaks
pos = find_max(pos_points , A1_cwt); % Detecting the +ve peak coefficients
neg = find_max(neg_points , -A1_cwt);% Detecting the -ve peak coefficients

figure,subplot(211)
plot(t,A1_cwt,pos,A1_cwt(pos),'*g',neg,A1_cwt(neg),'*r',...
    t,threshold,'--m',t,-threshold,':k','LineWidth',2)
xlabel('Time[ms]')
ylabel('Coefficient Amplitude')
title(...
    'Positive and Negative Peaks of CWT Coefficients After Thresholding',...
    'FontSize',16)
%legend('CWT Coefficients', 'Positive Peaks','Negative Peaks',...
%     'Upper Threshold','Lower Threshold')

subplot(212)
plot(t,A1_raw,pos,A1_raw(pos),'*g',neg,A1_raw(neg),'*r','LineWidth',2)
xlabel('Time[ms]')
ylabel('Original Signal Amplitude')
title('Detected Saccads','FontSize',16)

```

Wavelet decomposition for baseline drift removal:

```

function [baseline_remove] = wavdecomp( signal )
%Wavelet decomposition for baseline drift removal

```

```

wave = 'rbio6.8';
t1 = 1:size(signal,2);
level = 12 ;
[c0,i0] = wavedec(signal,level,wave);
cD1 = detcoef(c0,i0,1);
cD2 = detcoef(c0,i0,2);
cD3 = detcoef(c0,i0,3);
cD4 = detcoef(c0,i0,4);
cD5 = detcoef(c0,i0,5);
cA5 = appcoef(c0 ,i0,wave,5);
D1 = wrcoef('d',c0,i0,wave,1);

```

```

D2 = wrcoef('d',c0,i0,wave,2);
D3 = wrcoef('d',c0,i0,wave,3);
D4 = wrcoef('d',c0,i0,wave,4);
D5 = wrcoef('d',c0,i0,wave,5);
D6 = wrcoef('d',c0,i0,wave,6);
D7 = wrcoef('d',c0,i0,wave,7);
D8 = wrcoef('d',c0,i0,wave,8);
D9 = wrcoef('d',c0,i0,wave,9);
D10 = wrcoef('d',c0,i0,wave,10);
D11 = wrcoef('d',c0,i0,wave,11);
D12 = wrcoef('d',c0,i0,wave,12);
A12 = wrcoef('a',c0,i0,wave,12);

baseline_remove = D1+D2+D3+D4+D5+D6+D7+D8+D9;

figure,plot(t1,signal,t1,baseline_remove,'LineWidth',1)
xlabel('Time[ms]')
ylabel('Amplitude')
title('Flitered Data After Baseline Removal','FontSize',14)
legend('Original','Baseline Removed')

end

```

Plotting The threshold on CWT transformed Function

```

function [start_pos ,ending_pos, start_neg, ending_neg ] = plot_thresh(
X_cwt, X_final ,thresh )

%Ploting The threshold on CWT transformed Function

start_pos=[];
ending_pos =[];
start_neg=[];
ending_neg =[];
size(X_cwt,2);
flag_p = 0;
flag_n = 0;
for j = 2 : size(X_cwt,2)-1

    if(X_cwt(j)>=thresh)

        if(X_cwt(j-1)<thresh)

            start_pos =cat(2,start_pos, j);
            s_prev_p = j;
            flag_p =1;

        end

        if(X_cwt(j+1)<thresh)

            if(flag_p == 1 && ((j-s_prev_p)>1) )
                ending_pos = cat(2,ending_pos,j);
            end
        end
    end
end

```

```

        flag_p = 0;

        else
            start_pos = start_pos(1:size(start_pos,2)-1);
        end

    end
end
if(X_cwt(j)<=-thresh)

    if(X_cwt(j-1)>-thresh)

        start_neg =cat(2,start_neg, j);
        s_prev_n = j;
        flag_n =1;
    end
    if(X_cwt(j+1)>-thresh)

        if(flag_n == 1 && ((j-s_prev_n)>1) )
            ending_neg = cat(2,ending_neg,j);
            flag_n = 0;

        else
            start_neg = start_neg(1:size(start_neg,2)-1);
        end

    end
end
end

t = 1:size(X_final,2);

figure,plot(t,X_cwt,'LineWidth',2)
hold on
plot(start_pos,X_cwt(start_pos),'r*')
hold on
plot(ending_pos,X_cwt(ending_pos),'g*')
hold on
plot(ending_neg,X_cwt(ending_neg),'b*')
hold on
plot(start_neg,X_cwt(start_neg),'y*')
hold on
plot(t,thresh,'--m',t,-thresh,'--k');
title('Thresholding on CWT Coefficients ','FontSize',14)

end

```


Finding the positive and Negative peaks of CWT transformed Signal

```
function [ peak_indices ] = find_max( points, x_cwt)
%Finding the positive and Negative peaks of CWT transformed Signal

peak_indices = zeros(1,size(points,2));
for i=1:size(points,2)

    start = points(1,i);
    ending = points(2,i);
    if(ending-start>1)

        [C,I] = max(x_cwt(start:ending));
        peak_indices(1,i) = start+I;
    end

end

%t = 1:size(x_cwt,2);

%figure,plot(t,x_cwt,peak_indices,x_cwt(peak_indices),'*r')

end
```