ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

İbrahim Sefa ÖZYEŞİL

DEVELOPMENT OF TEXT SYNTHESIS SOFTWARE UTILIZING EEG SIGNALS

DEPARTMENT OF BIOMEDICAL ENGINEERING

ADANA-2019

ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

DEVELOPMENT OF TEXT SYNTHESIS SOFTWARE UTILIZING EEG SIGNALS

İbrahim Sefa ÖZYEŞİL

Msc THESIS

DEPARTMENT OF BIOMEDICAL ENGINEERING

We certify that the thesis titled above was reviewed and approved for the award of degree of the Master of Science by the board of jury on.

………………….	……………………………….	…………………………….....
Prof. Dr. Mutlu Avcı	Dr.Öğr. Üyesi Zehan KESILMIŞ	Dr.Öğr. Üyesi Ahmet AYDIN
SUPERVISOR	MEMBER	MEMBER

This MSc Thesis is written at the Department of Institute of Natural And Applied Sciences of Çukurova University.
Registration Number:

Prof. Dr. Mustafa GÖK
Director
Institute of Natural and Applied Sciences

This thesis was supported by the Scientific Research Project Unit of Çukurova University for my thesis (Project Number:).

ABSTRACT

MSc THESIS

DEVELOPMENT OF TEXT SYNTHESIS SOFTWARE UTILIZING EEG SIGNALS

İbrahim Sefa ÖZYEŞIL

ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES
DEPARTMENT OF BIOMEDICAL ENGINEERING

Supervisor : Prof. Dr. Mutlu AVCI
Year: 2019, Pages: 91
Jury : Prof. Dr. Mutlu AVCI
: Asst. Prof. Dr. Zehan KESILMIŞ
: Asst. Prof. Dr. Ahmet AYDIN

The brain-computer interface is one of the critical values that brings opportunities to understand human-computer interaction within a more direct approach. In Human Brain, there are discovered, and undiscovered mysteries exist.

An electroencephalogram (EEG) is a type of signal that shows the numerical values electrical activity of the brain. One of the essential EEG standards that discovered in BCI systems is the P300 signal.

Wearable BCI headsets technologies are growing day by day. Many wearable EEG headset technologies provide to discover human brain mysteries. OpenBCI is one of the low-cost EEG headsets that allows measuring EEG signals.

Day by day, artificial intelligence is taking place in human life. There are many new methods, and Technologies are developed to make people's life easier. Artificial intelligence methodologies play a vital role during the development of BCI applications.

The aim of this thesis, predicting mouse cursor movements of the computer via artificial intelligence methods using electroencephalogram signals which are provided by OpenBCI wearable headset.

Keywords : The Brain Computer Interface, Electroencephalogram, OpenBCI, Artificial Intellegence.

ÖZ

YÜKSEK LİSANS TEZİ

EEG İŞARETLERİNİN KULLANIMI İLE METİN SENTEZLEME YAZILIMI GELİŞTİRİLMESİ

İbrahim Sefa ÖZYEŞİL

ÇUKUROVA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ
BİOMEDİKAL MÜHENDİSLİĞİ ANABİLİM DALI

Danışman : Prof. Dr. Mutlu AVCI
Year: 2019, Pages: 91
Jüri : Prof. Dr. Mutlu AVCI
: Dr.Öğr. Üyesi Zehan KESILMIŞ
: Dr.Öğr. Üyesi Ahmet AYDIN

Beyin-bilgisayar arayüzü, insan-bilgisayar etkileşimini daha doğrudan bir yaklaşımla anlama fırsatını sağlayan kritik değerlerden biridir. İnsan beyninde, keşfedilmiş ve keşfedilmemiş gizemler var.

Bir elektroensefalogram (EEG), beynin elektriksel aktivitesinin sayısal değerlerini gösteren bir sinyal türüdür. Beyin Bilgisayar Arayüzü sistemlerinde keşfedilen temel EEG standartlarından biri P300 sinyalidir.

Giyilebilir BCI kulaklık teknolojileri gün geçtikçe artmaktadır. Giyilebilir birçok EEG kulaklık teknolojisi, insan beyni gizemlerini keşfetmeyi sağlar. OpenBCI, EEG sinyallerini ölçmeyi sağlayan düşük maliyetli EEG kulaklıklardan biridir.

Gün geçtikçe yapay zeka insan yaşamında gelişiyor. Birçok yeni yöntem mevcut olup ve teknolojiler insanların hayatını kolaylaştırmak için geliştirilmektedir. Yapay zeka metodolojileri, beyin-bilgisayar arayüz uygulamalarının geliştirilmesinde hayati bir rol oynamaktadır.

Bu tezin amacı, bilgisayarın fare imleci hareketlerini OpenBCI giyilebilir kulaklıkla sağlanan elektroensefalogram sinyallerini kullanarak yapay zeka yöntemleriyle tahmin ederek metin sentezleme yapmaktır.

Anahtar Kelimeler: Beyin Bilgisayar Arabirimi, Elektroensefalogram, OpenBCI, Yapay Zeka.

EXTENDED ABSTRACT

People can express themselves in a variety of ways, such as speaking, writing, painting, pointing, and transferring the message. In this context, the human-computer interface is the field of work that is developing day by day to better recognize the human brain by enabling the connection between the mind and the signal from the brain. The interface provides a communication path between the brain and the human

Various studies try to make sense of the signals coming from brain neurons, both to better understand the human brain and to facilitate the lives of people.

Stuart K. Card first used Human-computer interaction in the 1983 book The Psychology of Human-Computer Interaction.

By increasing the usability of the human-computer interface, social computer interaction is gradually growing. There are different working areas in this field.

Day by day, artificial intelligence has a more significant role in human life. Many new approaches are available, and technologies make people's lives easier. Technologically, areas such as software, hardware, and physical design are involved and increase the interaction with human beings in psychological, communicative, sociological, and organizational aspects.

Nowadays, with the process called Electroencephalogram (EEG), it is possible to transfer signals in real-time with electrodes placed at specific positions of the head. According to these signal changes, individual response measurements are observed.

EEG (Electroencephalogram) signals are used in many applications. With this increase in use, EEG measurement systems have gradually increased depending on the need. OpenBCI is a low-cost EEG device category that allows us to receive EEG signals through an interface and better recognize the human brain.

The aim of this thesis is to manage computer mouse cursor movements by interpreting signals from the OpenBCI wearable EEG device. By the mouse cursor management, it is desired to creating a flow for text syntesis.

GENİŞLETİLMİŞ ÖZET

İnsan, konuşma, yazı yazma, resim yapmak, işaret etmek gibi çok çeşitli yollar ile kendini anlatabilmekte ve anlatmak istediği mesajı karşısında olan insana aktarabilmektedir. Bu kapsamda, insan Bilgisayar arayüzü, beyin ve beyinden sinyal arasında bağlantı kurmayı sağlayarak, insan beynini daha iyi tanımamız için gün ve gün gelişmekte olan çalışmak alanıdır. Arayüz, beyin ile insandan gelen sinyal arasında iletişim yolu sağlamaktadır.

Beyin nöronlarından gelen sinyalleri anlamlandırmaya çalışılarak, hem insan beyninin daha iyi anlaşılması, hem de insanların hayatlarını kolaylaştırılan çeşitli çalışmalar mevcuttur.

İnsan bilgisayer etkileşimi ilk kez 1983 yılında yayınlanan The Psychology of Human Computer Interaction adlı kitapta Stuart K. Card tarafından kullanılmıştır.

İnsan bilgisayar arayüzünün kullanıllırlığı arttırılarak, insan bilgisayar etkileşimi giderek artmaktadır. Bu konu ile çeşitli alanlarda çalışma alanları mevcuttur.

Gün geçtikçe yapay zeka insan yaşamında daha büyük bir rol almaktadır. Birçok yeni yaklaşım mevcut olup ve teknolojiler insanların hayatını kolaylaştırmaktadır. Teknolik açıdan, yazılım, donanım ve fiiziksel tasarım gibi alanlar da işin içine girerek, insan ile olan etkişilimi, psikolojik, iletişimsel, sosyolojik ve organizasyonel açıdan arttırmaktadır.

Günümüzde Elektroansefalograif (EEG) adı verilen işlem ile birlikte, kafanın belirli pozisyonlarına yerleştirilen elektrotlar ile gerçek zamanlı olarak sinyal aktarımı yapılabilmektedir. Bu sinyal değişikliklerine göre de bireyin tepki ölçümleri gözlenmektedir.

EEG (Elektroensefalogram) işaretleri bir çok uygulama alanında kullanılmaktadır. Bu kullanımın da artması ile birlikte EEG ölçüm sistemleri de ihtiyaca bağlı olarak giderek artmıştır. OpenBCI, EEG sinyallerini bir arayüz aracılığı ile almamızı sağlayan bir cihaz olup, insan beynini daha yakından tanımamıza olanak sağlayan düşük bütçeli EEG cihazlı kategorisindedir.

Bu tezin amacı, bilgisayarın fare imleci hareketlerini OpenBCI giyilebilir EEG cihazı üzerinden gelen sinyalleri anlamlandırarak yönetmek. Yönetilen fare imleci ile de metin sentezleme çalışması yapmaktadır.

ACKNOWLEDGEMENTS

There are many people to think during this thesis period. However, there are some game-changer events that I would like to announce them here.

First of all, My Academic Advisor, Prof. Dr. Mutlu Avcı. He was the one who gave me this opportunity the work with him. It is a great pleasure to learn even small breadcrumb from his wisdom.

Secondly, during this period, my company Authority Partners allowed me to be their Remote Quality Assurance Analyst. They provided me the opportunity to continue my master's of science program in the journey. I want to thank especially Haris Budjevac, Selma Emirhafızovic, and Emek Taydaş for making me do the first step to join AP. Another unique value in this period, my team that I am currently involved in. I have learned a lot from my team lead Ibrahim Kujrakovic on how to be calm in unexpected circumstances. Other team members who became family to me, Fabio Rodrigo Luz, Besim Durguti, Mittal Bhadra Chandra, Selma Vucijak, thanks to them keeping me happy when I am working with them.

For good measure, I would like to thank my other colleagues from Authority Partners. Firstly my mentor, Emir who helped me to adapt my work and made me feel like home. Secondly, Mehrudin Herceg, who is one of the most patient quality assurance analyst. He always gave me a clear explanation of his calmness. Another valuable member is that Vitalii Riabko, who works with me in the same position in different teams. His positiveness and friendship always made my day better.

My architect, Amra Hadzibajiric, she is one of the best people with a big kind heart. When you go to her, she never lets you down. She always helps you out in your limbo when you have some technical difficulties. Not only those but also she is a perfect trainer who helps you to improve your professional skills step by step.

My Project Manager, Eldar Jordamovic, who always listens to the solution of narrow passes during release cycles. Besides, my scrum master, Benjamin Sahacic, who joined to AP couple months ago but made us feel like, he has been with us since the beginning. Thank you to them for letting me take more responsibility.

Furthermore, I would like to my friends who helped out to manage in this process patiently. First of all, Ali Kıral, who has always motivated me while writing those papers. Another appreciation to my friends who are a lecturer at university. Mustafa İstanbullu, Erkan Ödemiş, Cemil Keskinoğlu, and Mehmet Sarıgül our scientific discussions always kept me up to date. It was as a young football player's first day on the football pitch.

During this period, Harry Potter movies, silverback gorilla videos, Fenerbahçe were one of the most motivating different mindsets for me.

After all this time?

Always…

CONTENTS **PAGE**

LIST OF FIGURE **PAGE**

ABBREVIATIONS LIST

ANN	: Artificial Neural Network
EEG	: Electroencephalogram
FFNN	: Feed-Forward Neural Network
BCI	: Brain Computer Interface
HCI	: Human Computer Interaction
NIRS	: Near Infra Red Spektroskopsy
fMRI	: Functional resonance imaging
ALS	: Amyotrophic Lateral Sclerosis
DM	: Data Mining

1. INTRODUCTION

1.1. Human Computer Interaction

(Cuntai Guan *et al.*, 2006)Practical and theoretical studies in the field of Human-Computer Interaction (HCI) aim to produce information and communication technologies for human and human needs. Human Factors, a new interdisciplinary field that emerged in the 1970s and spread rapidly at the end of the 1990s, and it is the most popular part, "Human-Computer Interaction (HCI) mak eliminate or minimize these problems works for. Experts in the field of Human-Computer Interaction are working on how to create more usable or user-transparent information technology systems. As the name implies, it includes both technology and human in HCI. In terms of technology, areas such as software, hardware, and physical design are involved, and for human beings, psychology, communication, sociology, and organizational sciences are all familiar with. This naturally requires the contribution of many academic disciplines to HCI. Among these, psychology, cognitive sciences, informatics, ergonomics, organizational sciences, education, computer science, and sociology are the first to come to mind. It is still debated whether HCI is a separate field of science due to its influence from different disciplines and borrowing many fundamental concepts and theories from these disciplines. In addition to those who claim to be a sub-branch of Software Engineering or Psychology, there are also individuals who claim that HSE is a new interdisciplinary field.

1.2. Brain Computer Interface

(Zhang and Deng, 2014)Brain-Computer Interface (BCI) is a platform through which people communicate with a computer directly using their brain signals. BCI is perhaps the only way that people with a lack of control of their peripheral nerve and muscles could use to communicate with the outside world using a computer.

(Chiesi *et al.*, 2019)Due to its non-invasive nature, electroencephalography (EEG) It is still the most utilized signal among existing BCI signals. In order to develop BCI systems, various signals can be extracted from EEG such as slow cortical potential, μ and β rhythms, synchronization, and desynchronization evoked by motor imagery, P300 evoked potential, static-state visual evoked potentials.

(Guan, Thulasidas and Wu, 2004)The objective of the brain-computer interface (BCI) is to establish the user's intention by observing and analyzing brain activity in the absence of being dependent on signals generated by muscles and peripheral nerves. Researchers usually utilize electroencephalography (EEG) to identify brain activity and they use electrocorticography (EcoG), near-infrared spectroscopy (NIRS), or functional resonance imaging (fMRI). Due to its properties such as being noninvasive, portable, and suitable for use in almost any environment and along with its having excellent time resolution, EEG is the most common technique. A complicated series of data-processing steps are involved in identifying the user's intention whose strength is dependent upon its weakest link.

(Zhang and Deng, 2014)The electrical events of the brain is saved via electrophysiological monitoring method called electroencephalography (EEG) in which a set of electrodes are placed along the scalp of a subject. In diagnosing diseases such as epilepsy, sleep disorder, coma, etc., EEG is used, besides, Brain-Computer Interface (BCI), neurofeedback and rehabilitation are all included in recent applications. A soaring number of hardware and software solutions for BCI have been developed in the last couple years, including innovative electrodes, novel stimuli presentation methods, new algorithms, new software, and new applications. Signal acquisition and processing frameworks which are either custom made systems that allow maximum flexibility in manipulating and gaining access to internal blocks or commercial systems aiming at speeding up development are relied upon in those works. Commercial systems are systems whose hardware and often software are not accessible by the user and thus cannot be modified. Research groups developing new BCI systems can suffer from this.

The cost is another issue for such research groups. The number of devices, performing tests running more than a couple of hours, and the number of subjects on which experiments to be conducted is limited for them.

1.3. Data Preprocessing

Data mining (DM) stands out as an interdisciplinary discipline that has started to spread rapidly in the world in the last ten years. Nowadays, the increasing number of data, the spread of computer use, and the steps towards becoming an information society will bring this discipline to the agenda more. Data mining, which has a widespread use abroad, is being applied and understood in our country. As the quality of the data to be used in data mining will also affect the results, pre-processing of the data to be used is very important. Quality data will ultimately produce quality outputs. (Sun, Hu and Liu, 2014) The way to improve the quality of data can be achieved by pre-processing the data quality. This pre-processing of data plays an essential role in the study based on human-computer interaction.

1.4. EEG Filters

The utilization of filters has a crucial role in recording and displaying EEG signals and in generating understandable EEG traces. If it were not for filters lots of segments of EEG recordings would not be comprehensible. As it will be seen in the present chapter that filters may have an impact on the EEG signal, small or large. Filters tidy the EEG tracing and make it readable. Particular filter settings emphasize certain EEG activity. However the improper use of filters can result in unwanted consequences.

Some people view the working principle of filters as a boring field. The primary goal of present chapter is furnishing the student with an introductory overview of the way EEG filters work so an EEG technologist and reader can utilize EEG filters in a suitable way. A part is devoted to a discussion of simple circuit design a natural part of electroencephalography training. Methods used in filtering digital EEG signals are also considered. In-depth knowledge is not needed to understand and explain EEGs but understanding the filter algorithms boosts the insight into filter behavior and EEG interpretation.

Figures 1.1 and 1.2 shows the result of the work of filters upon an EEG signal. In Figure 1.1 an EEG record is shown with a modest subject movement. No filtering is applied on this data. Figure 1.2 shows the same data after filtering. Muscle artifact destroys bottom and top four lines of EEG (The temporal areas), but with filtering the amplitude of muscle activity is attenuated which makes it easy to notice adjacent channels. In muscle artifact (which stems from the contraction of the temporalis muscles) there are intermittent waves and if it were not for the filters these waves would not be detected. The baseline of every channel is straighter and the fact that every channel tends to remain in its horizontal area after filters are used makes the interpretation easy.

There are some disadvantages regarding the picking of filter settings. One might think that if a particular filter configuration does a good job filtering messy data then a more aggressive adjustment will does better. This is not the case for filters because filtering actually is losing information and excessive operation of filters may discard data which potentially be of interest to the reader. Particular configuration of filters can alter the shape of brain waves and mislead the reader into thinking that there are waveforms that are non-existent.

1.4.1. The Fundamental Approach To Deciding Filter Configurations

An optimal filter would clean the EEG tracing off all electrical interference or artifact and solely lets cerebral activity out. There is no such filter and existing filters only discard waves in accordance with mathematical rules. However through simple mathematical assumptions, it is possible to filter particular components of EEG signals. The brain can only generate EEG waves within a particular frequency range so any other wave whose range (possibly too fast or too slow) falls outside of that of brain cannot stem from cerebral activity. In general, when designing filters it is assumed that activities which fall outside of 1-Hz –35-Hz are not brain activities and are often regarded as electrical noise or artifact. This is usually the case, but not always. Typically, EEG filters are so designed that one of the filters reject most of very high-frequency activity while the othe filter reject most of very low-frequency activity. Frequencies that are allowed to pass are called the bandpass.

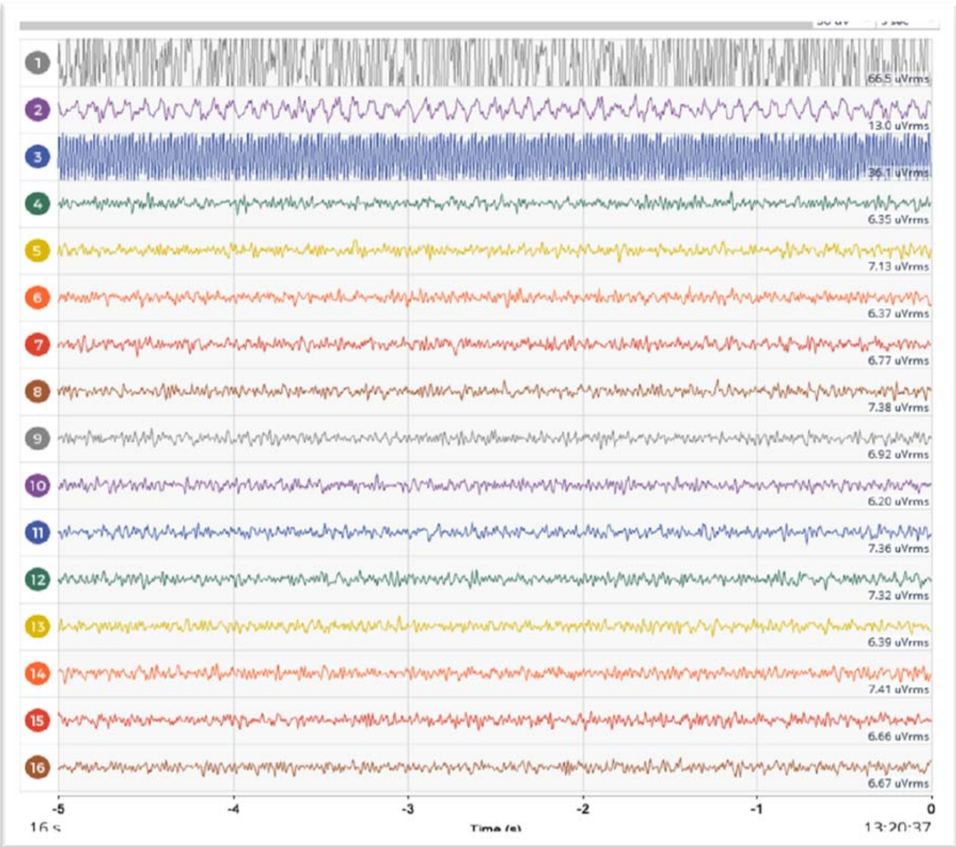


Figure 1.1. RAW Data of EEG

In the lack of filters was this EEG record obtained. Considerable amount of temporal chain is destroyed by muscle artifact. So large a flactutation do the baselines of some channels exhibit that they destroy other channels.

Through utilizing filtering methods we can make EEG activity appear which can hide behind large activity of voltage. The electroencephalographer deliberately reduces the slower activity (true cerebral activity) to make fast activity appear because that fast activity would disappear within waves of high voltage. In Figures 1.3 and 1.

4 such filtering is depicted. Note that this filtering technique is not used in every EEG reading. Observing those figures, one can see the way in which the low frequency filter is aggressively utilized and spike-wave discharges are brought out.

1.4.2. Types Of Filters

Three very common filters are in use in clinical EEG. Those are low-frequency, high-frequency and notch filters. A low-frequency filter does not let low-frequencies pass. Engineers call low-frequency filters high-pass filters because low-frequency filters only allow high frequency signals to pass. High-frequency filters work the opposite way and they are referred to as *low-pass filters. The two terms are common in electrical engineering but not in clinical electroencephalography.* High-frequency filter and low-frequency filter are used instead and high filter (HF) and low filter (LF) are abbreviations for them.

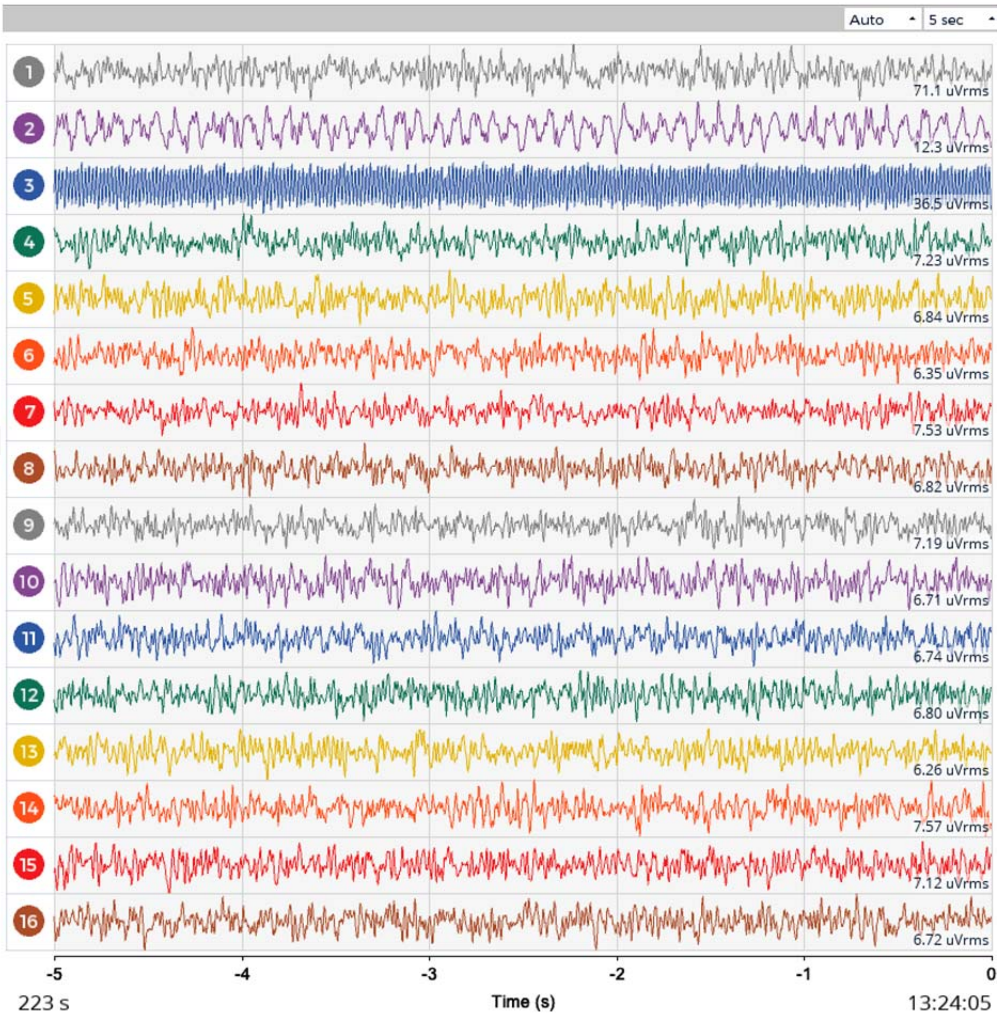


Figure 1.2. 10 Second EEG Record as in Figure 1.1

The notch filter does not work in a frequency range, it works in a particular frequency and allows only that frequency to pass. In North America, the frequency of alternating current is 60 Hz. That 60 Hz activity generates an electric field which interferes with EEG. This is where a notch filter comes into play and a 60 Hz notch filter discards unwanted 60 Hz signal. In another country whose line frequency is, say, 50 Hz, then a 50 Hz notch filter is used.

1.4.3. Filter Naming Conventions

Two naming conventions are used for high- and low- frequency filters. A frequency can be followed by a filter (e.g., a “5-Hz low filter”) or a filter can come after its time constant (e.g., a “low-filter with time constant of 0.1 seconds”). When a filter comes after a specific frequency, that frequency is called nominal frequency or cutoff frequency of the filter. It is up to the manufacturer to decide which naming will be used. The fact that the convention in which filters are referred to by ther cutoff frequencies is getting more widely used and cutoff frequencies are more comprehensible we will first deal with the relation between a filter’s electrical characteristics and its cutoff frequency.

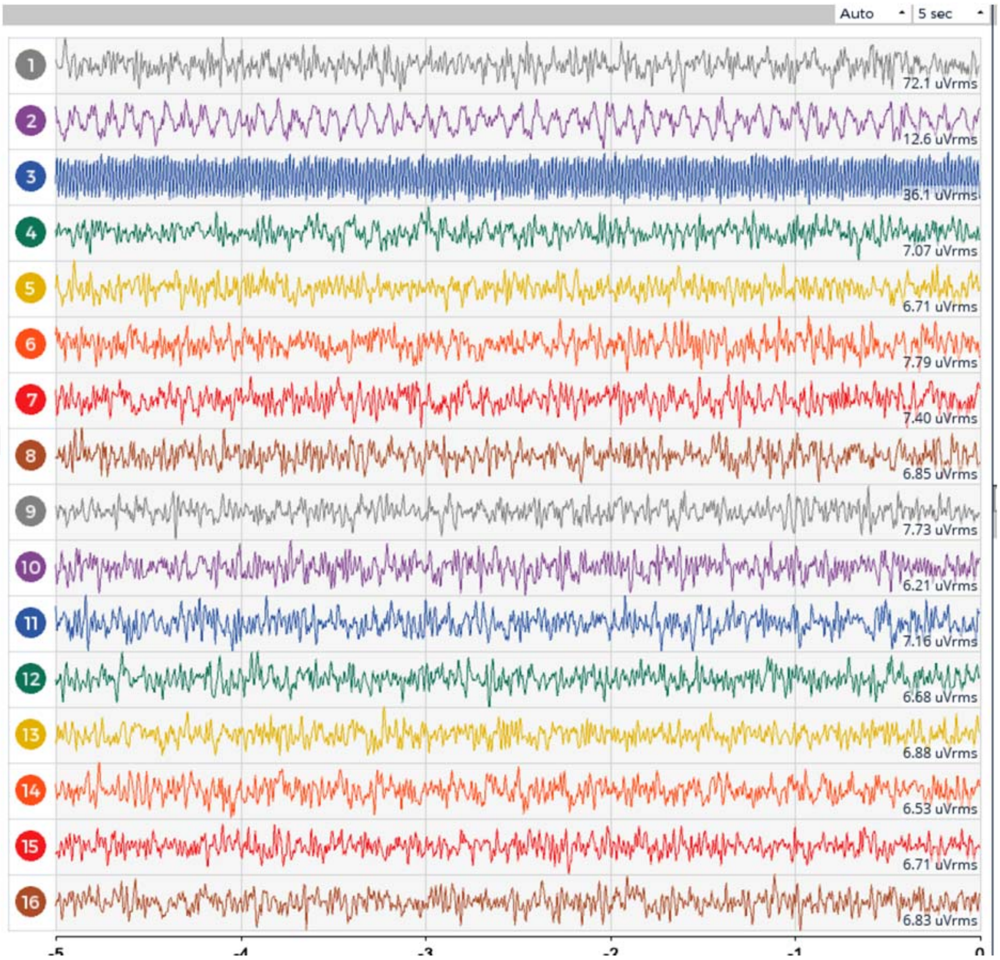


Figure 1.3. Low Frequency Filter

1.4.3.1. Low-frequency filters

Cutoff frequency makes one imagine an all-or-nothing situtation at the frequency mentioned. For example let there be a cutoff grade for an exam. Participants of the exam whose grades are below that cutoff grade cannot pass or go on. In an amusement park people above a cutoff height cannot take specific rides. The nature of low-frequency filters related to cutoff frequencies is not strict like teachers and amusement park officials at all. The way a filter involves in a signal activity is interesting. When a sine wave happens to meet a low-frequency filter whose frequency is the same as the cutoff frequency of the filter, that filter reduces the amplitude of the sine wave by approximately 30 %. The frequency of a sine wave with a lower frequency will be cut down more than by 30 %. The amount of attenuation of amplitude rises as the frequency of the wave goes lower than the cutoff frequency of a low-frequency filter. Which is more interesting that sine waves with larger frequencies than the cutoff frequency of low-frequency filters experience a cutdown in their amplitude by less than 30%. A sine wave is less affected as its frequency goes above the filters nominal frequency.

1.4.3.2. Visual Effects of Low-Frequency Filters

The objective of a standard low-frequency filter with cutoff frequency of 1 Hz or below is to make every EEG channel stay in its horizontal zone and eliminating large intrusions up and down into other channels' areas. This is due to the fact that baseline drifting stands for a low frequency wave. When more effective low-frequency filters whose cutoff frequencies are 3 Hz or 5 Hz are used they first attenuate delta frequencies. With higher frequency filters, some slow activity is almost eliminated and by this, other properties of EEG could be brought out. It should be noted that the baselines of channels assume a straight regime while maintaining faster activity as more restrictive settings for the low filter are implemented one after the other.

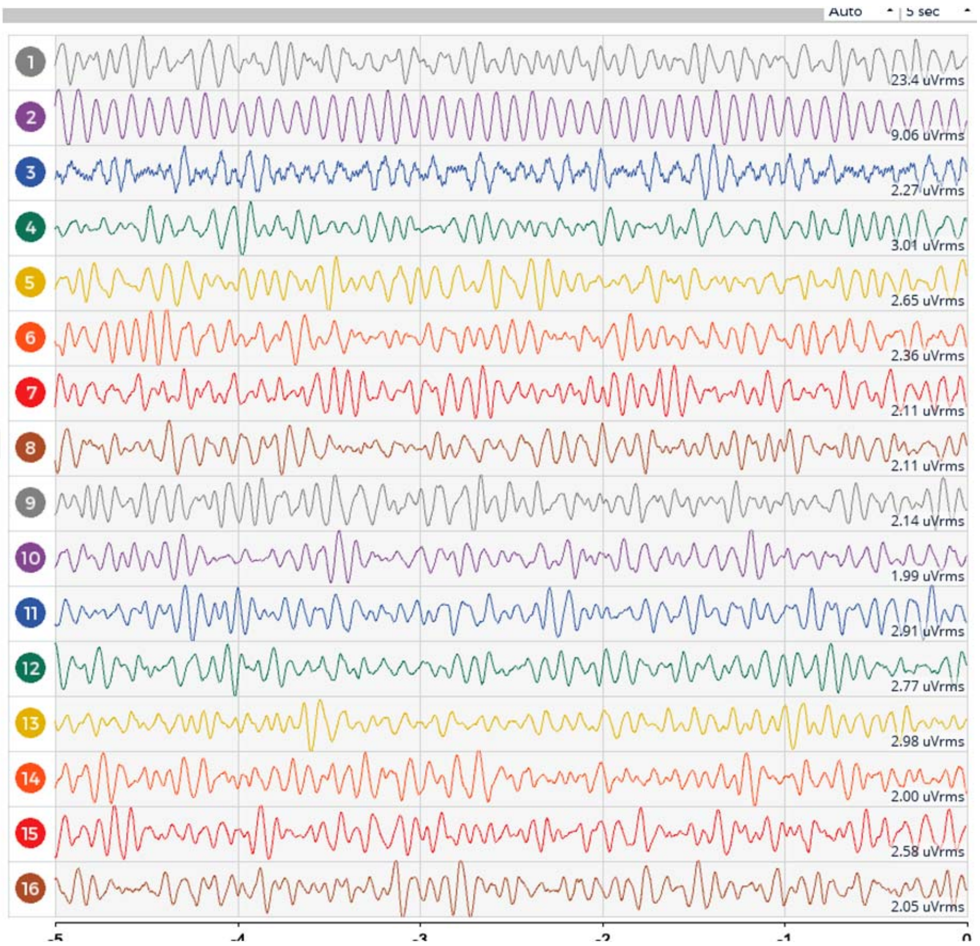


Figure 1.4. Low Filter Configuration for EEG Signals

1.4.3.3. High-frequency filters

High frequency filters have roll-off characteristics like low-frequency filters. In the case of high-frequency filters the curve rolls off in the opposite direction to that of low-frequency filters, decreasing toward the right. Like LFFs, an HFF applies a rate of 30% for attenuation at its nominal frequency. Waves of higher frequency go through a reduction in amplitude by greater than 30% while smaller frequency waves experience an attenuation not greater than 30%. Roll-off characteristics of theoretical 70-, 35-, and 15-Hz HFFs are shown. HFFs are particularly beneficial discarding muscle artifact and other high frequency noise. More than sufficient usage of high-frequency filters may change wave shape and this will lead wrong results. This case will be better understood in the discussion of time constraints.

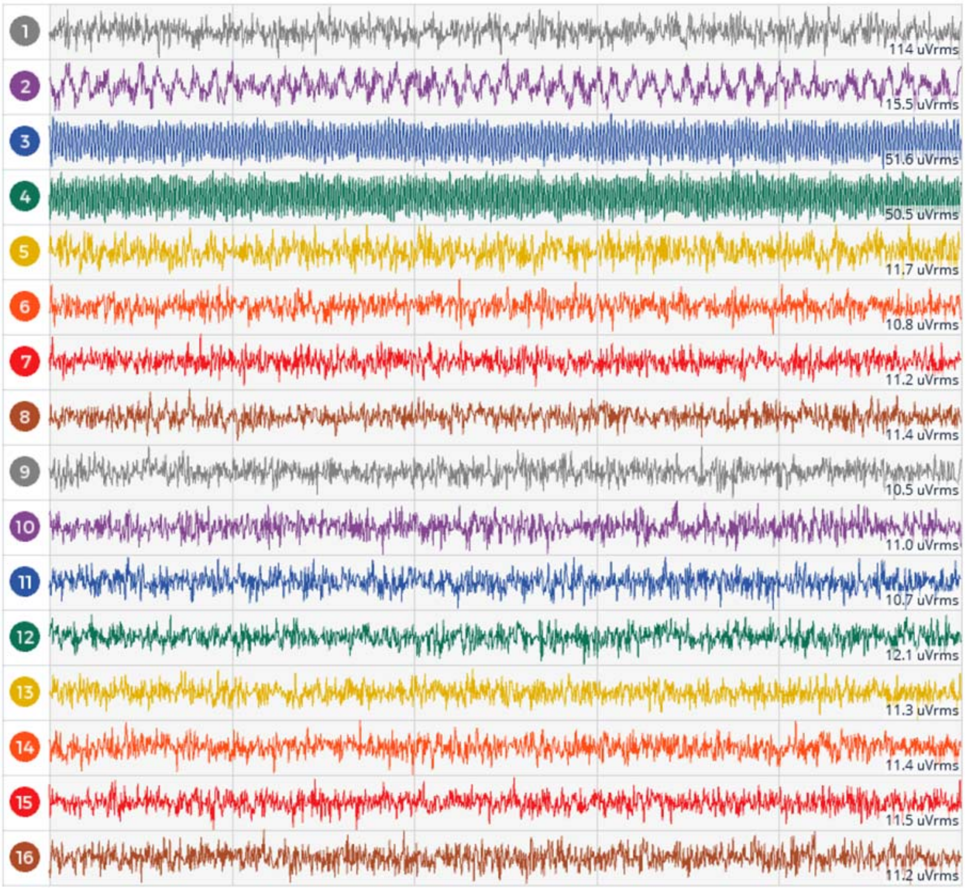


Figure 1.5. Sleep Mode Without Filter

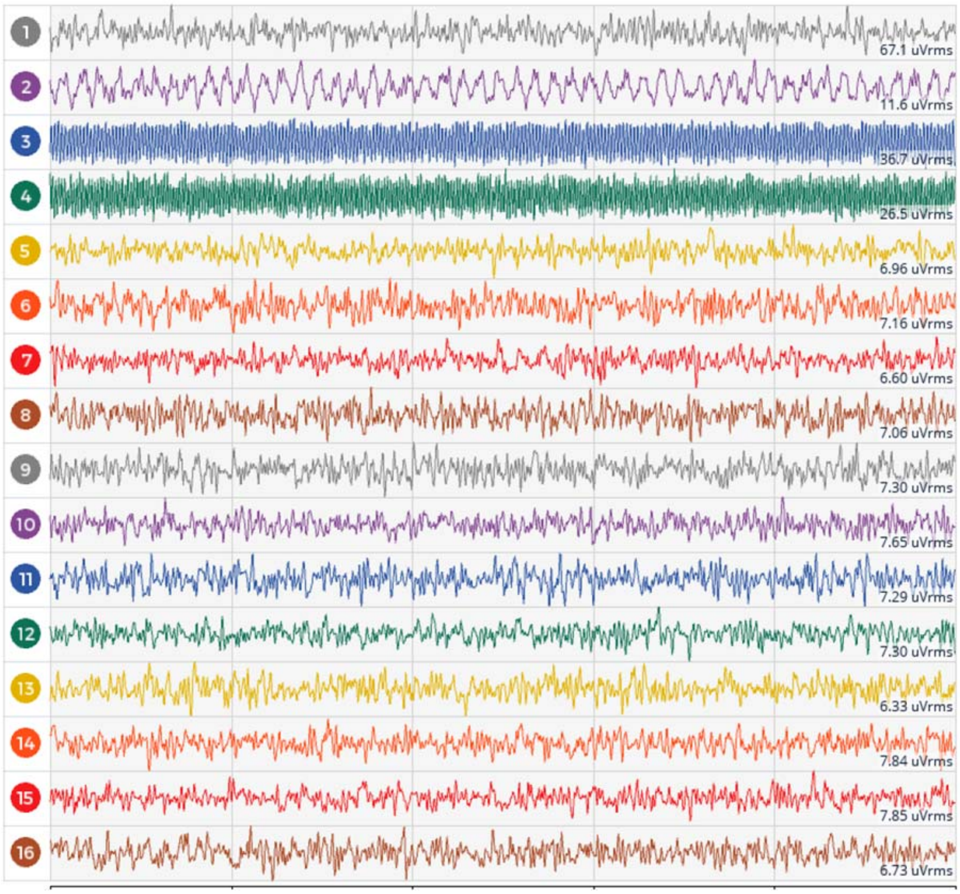


Figure 1.6. Sleep Mode with 1-50Hz Filter

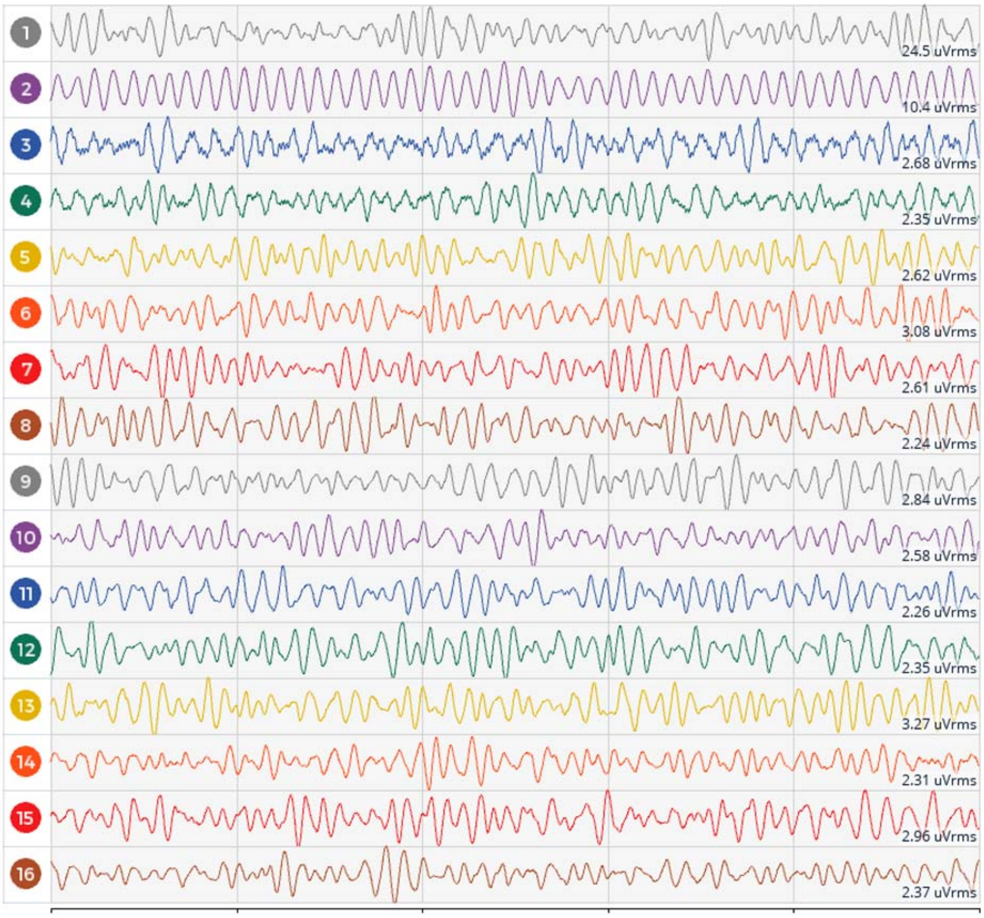


Figure 1.7. Sleep Mode With 7-13 Hz

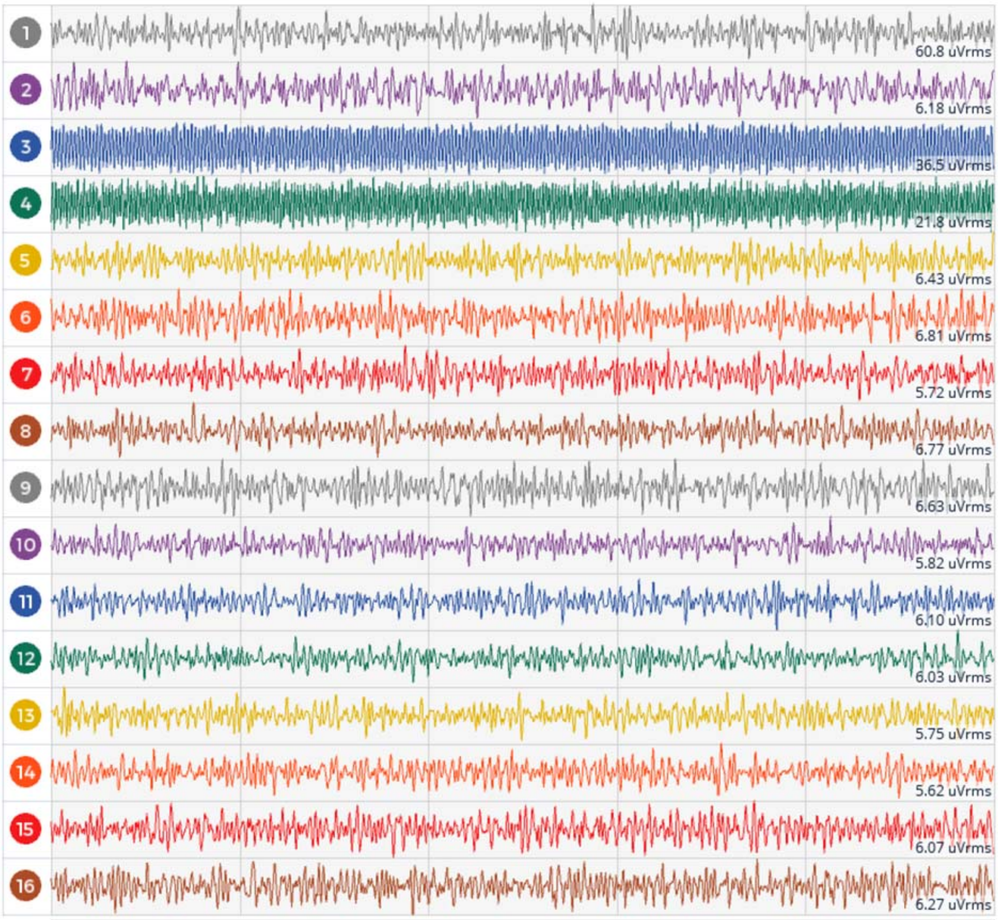


Figure 1.8. Sleep Mode With 15-50 Hz Filter

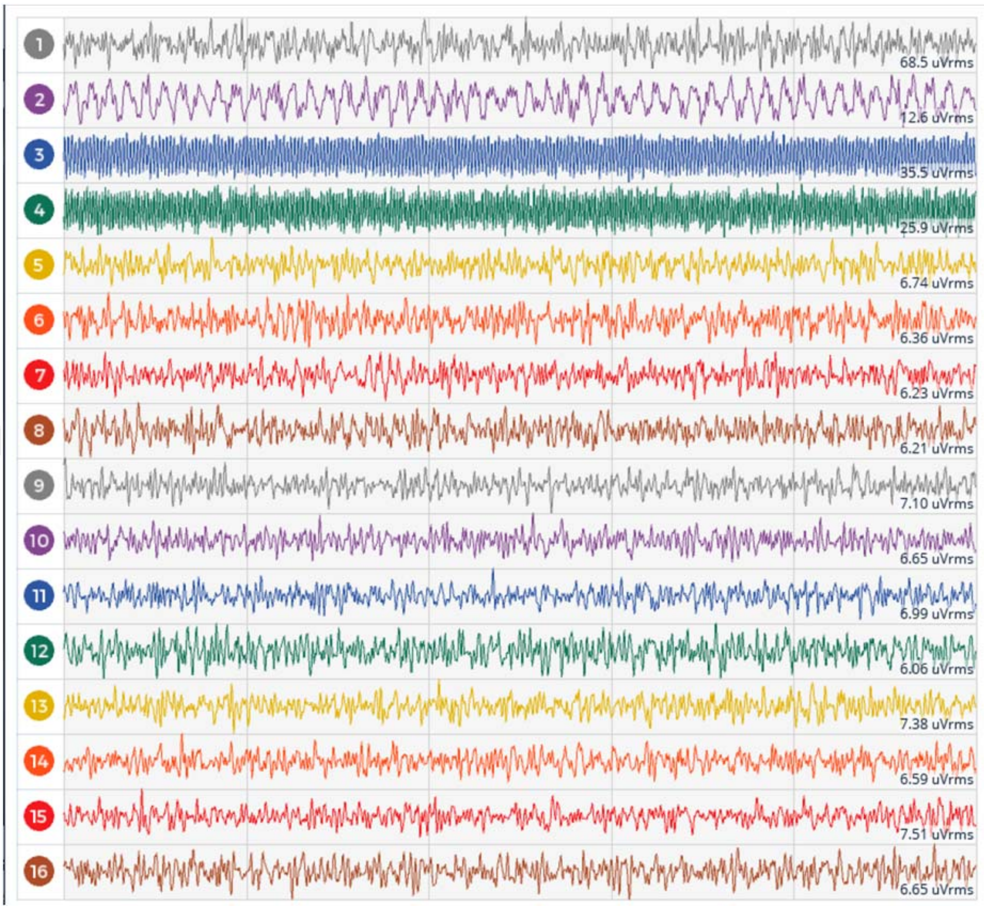


Figure 1.9. Sleep Mode With 5-50Hz Filter

1.4.4. Wave Attenuation And Decibels

The naming convention in which the filter comes after the attenuation frequency will be explained in this part. The amount of reduction in a wave by a filter can be expressed in decibels. The logarithm of the division of powers of two waves is a *bel* and multiplication of this number by 10 gives decibel:

$$dB = 10.\log\left(\frac{p_1}{p_2}\right)$$

in which p_1 and p_2 are the powers of the two waves.

The decibel unit is a comparison which means it is always stated with respect to a reference value. (This is also true for expressing the intensity of sound) In EEG, voltage measurements are used instead of power measurements while decibel measurement involves power of waves. Therefore we have to include amplitude of waves in the equation. The power of a wave equals division of amplitudes raised to the power of two. If we substitute amplitude for power:

$$dB = 10.\log\left(\frac{{a_1}^2}{{a_2}^2}\right)$$

in which a_1 and a_2 are the amplitudes of the two waves. Rewriting the equation:

$$dB = 20.\log\left(\frac{a_1}{a_2}\right)$$

The frequency where the *power* of a wave is reduced by 50% is referred to as the nominal or cutoff frequency of a filter. This frequency is also known as "3-dB point" It is 3 dB when the power falls back to its half, thus when p1 is double the value of p2. Ten times log(2) is 3.01. If power ratio is 2:1 then what is the ratio of amplitudes? Amplitudes are squared to get the power, the two waves would exhibit a 3-dB change in their amplitudes and that corresponds to approximately 70% attenuation in wave height.

$$10\log(10^2/7^2) = 10\ \log\left(\frac{100}{49}\right) \cong 3\ dB$$

The reason why cutoff frequency comes after the point where filter attenuates the power by 50% (the amplitude by 30%) is 50% reduction in power means 30% reduction in amplitude.

The extent of slope of the roll-off graphic can be expressed in *decibels per octave. Octave* belongs to the musical world. In Electrical engineering, an octave is the multiplying or dividing a wave frequency by the number two. (In music middle C is a tone at 256 Hz, while high C is one octave above middle C and has 512 Hz frequency) A simple high pass filter frequency-response curve roll off at a maximum of 6 dB per octave, but this rate is variable through the frequency band.

1.4.5. Bandpass Filters

The properties of HFFs and LFFs are usually exploited to develop a specific bandpass. Generally when recording EEGs LFF is configured at 1 Hz and HFF is configured at 70 Hz and they are used together. The behaviour of LFFs and HFFs is not absolute like activity smaller than 1 Hz and greater than 70 Hz cannot pass. It is of gradual nature. Therefore we can encounter some signals below 1 Hz and above 70 Hz.

1.4.6. 50 Hz And 60 Hz Notch Filters

A notch filter discards a particular frequency from an EEG signal as is not the case with HFFs and LFFs where these two have a gradual roll-off characterstic. EEG record is contaminated with AC signal stems from wiring and outlets around test subject and notch filters are very useful for cleaning the record. The transmission curve of an ideal notch filter is flat everywhere other than the nominal frequency point. At that point the curve has a notch and any wave that has the nominal frequency of the filter is attenuated. In real world notch filters do not work as perfect In Figures below 16 an EEG signal contaminated with a 60-Hz signal in multiple channels is shown. The detail of that 60-Hz contamination is illustrated. The reader should become skilful at detecting that 60-Hz signal which makes up the artifact of this type.

We can tolerate some disadvantages of notch filters -a 60-Hz notch filter attenuates close frequencies, 59 Hz and 61 Hz. The thing is, the cerebral rhythms which are under consideration remain in a slower range than those close frequencies are. Thus the attenuation of frequencies like 59-Hz and 60-Hz can be ignored. What is more, a notch filter may have a hard time dealing with so many 60-Hz activity. A 60-Hz notch filter is suitable for use where AC is supplied at 60 Hz. You cannot use a 50-Hz filter in North America.

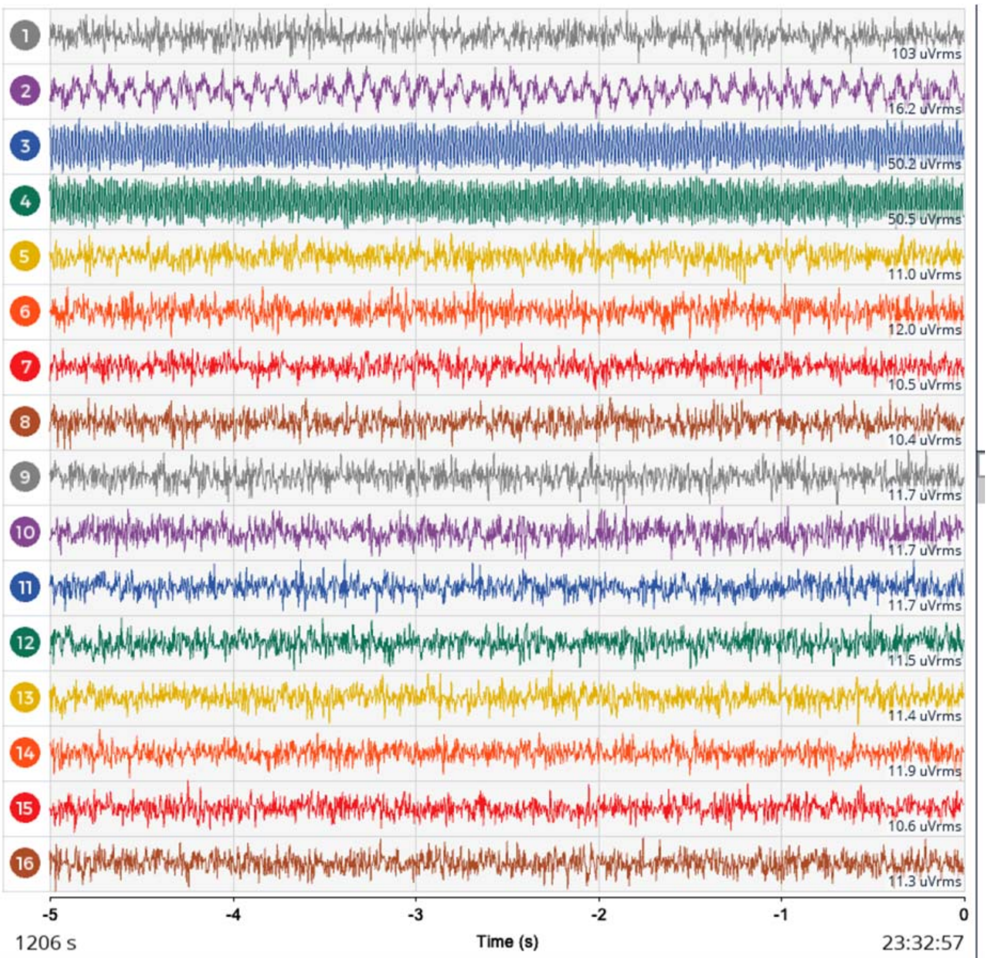


Figure 1.10. No Notch No Filter EEG Signals

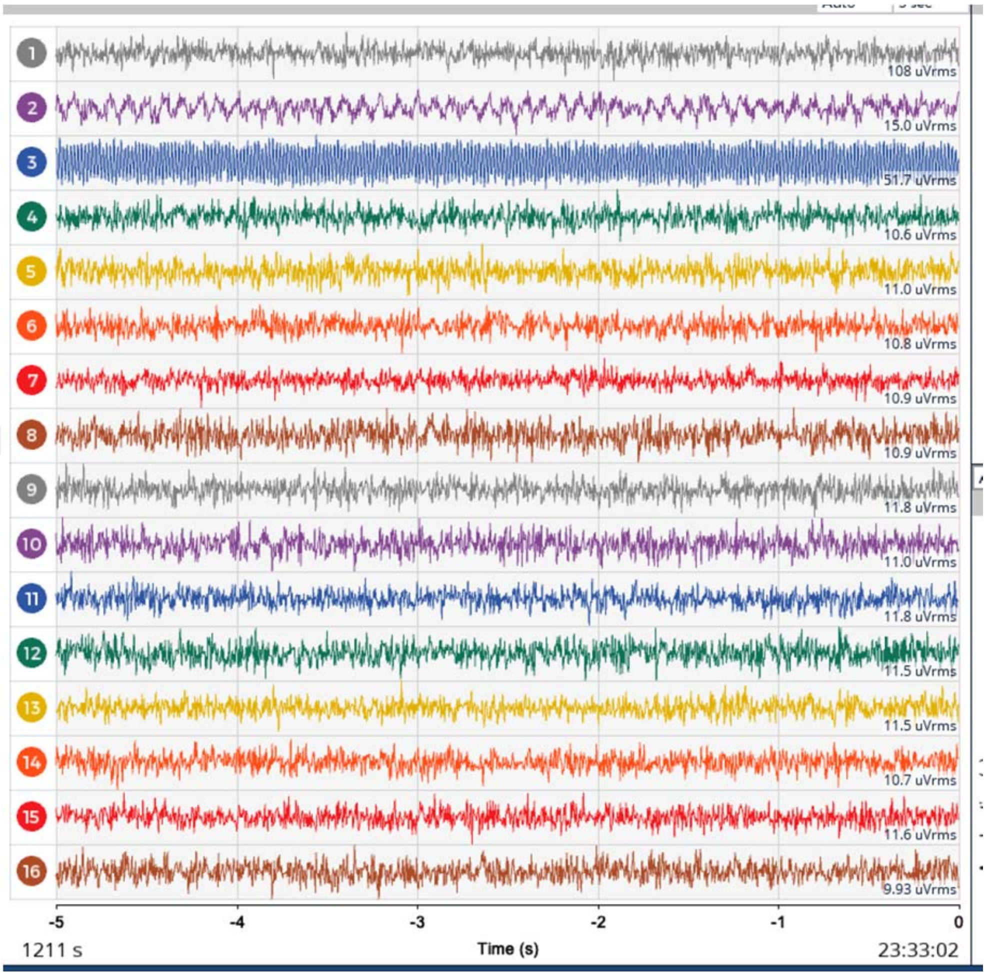


Figure 1.11. 60Hz Notch No Filter

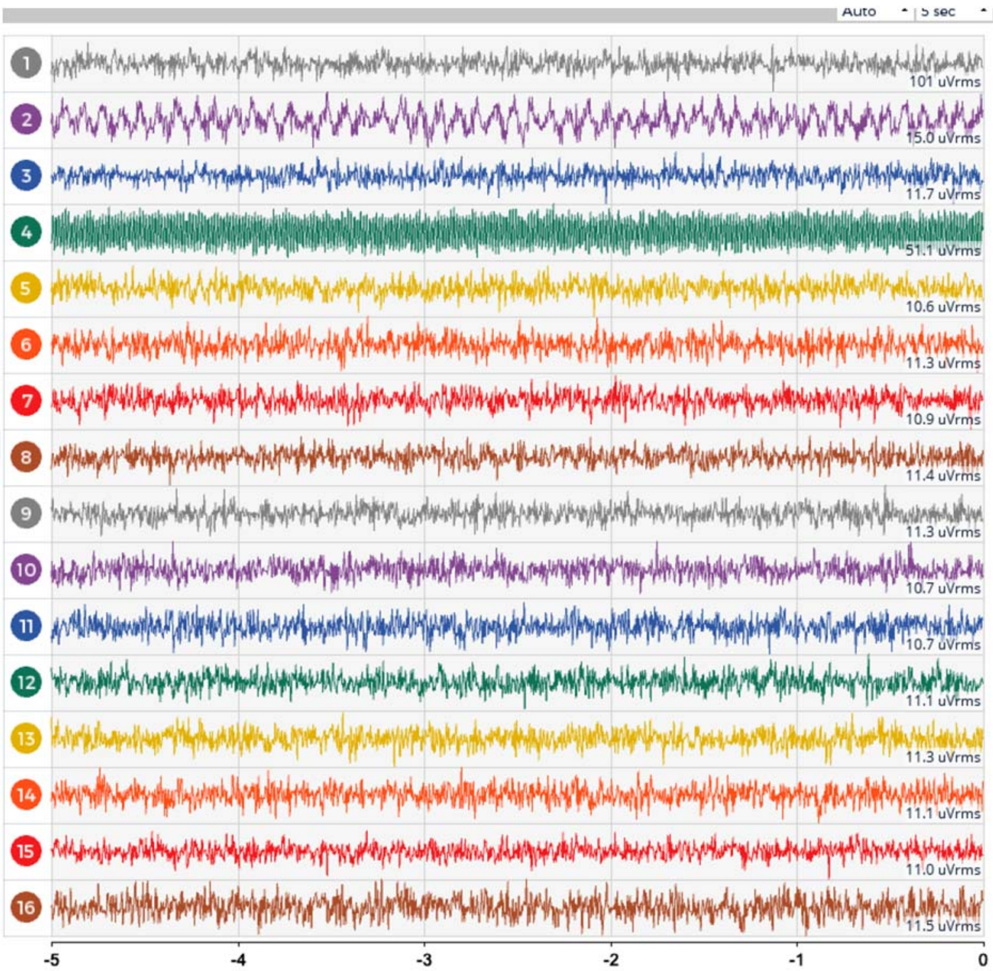


Figure 1.12. 50Hz Notch No Filter EEG

1.4.7. Digital Filters

Digital filter design which is complex and considered under digital signal processing is not within the range of this text. To have a general understanding of the working of filters, it is good to deal with some basic techniques about digital filters. RC circuits are analog devices and with the arrival of digital EEG instruments the methodologies utilized to design filters have totally changed. The waves we see on a digital EEG instrument are flow of numbers. Those tops are then connected to form a curve which is the EEG wave.

A person who is familiar with analyzing EEG waves would see two waves combined, a slow and and a fast one, a superimposition. A computer does not "see" what that person sees. The EEG instrument software is only a series of numbers to the computer.

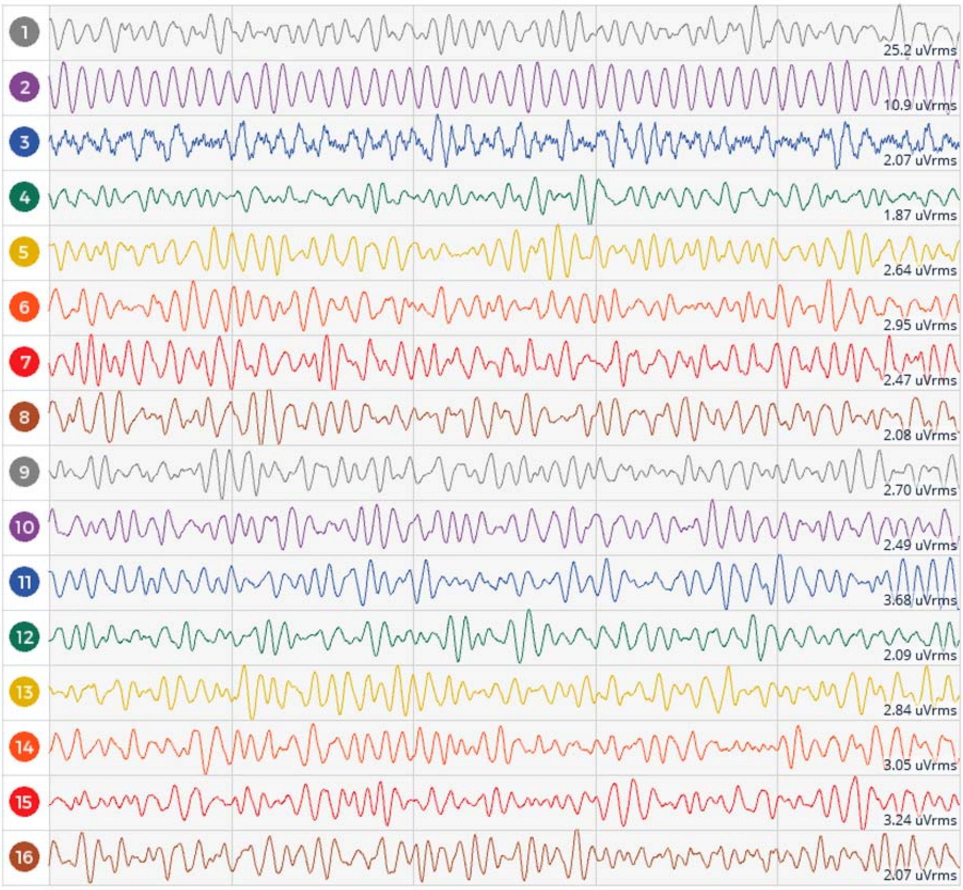


Figure 1.13. EEG Data with 30 FPS Sampling Rate

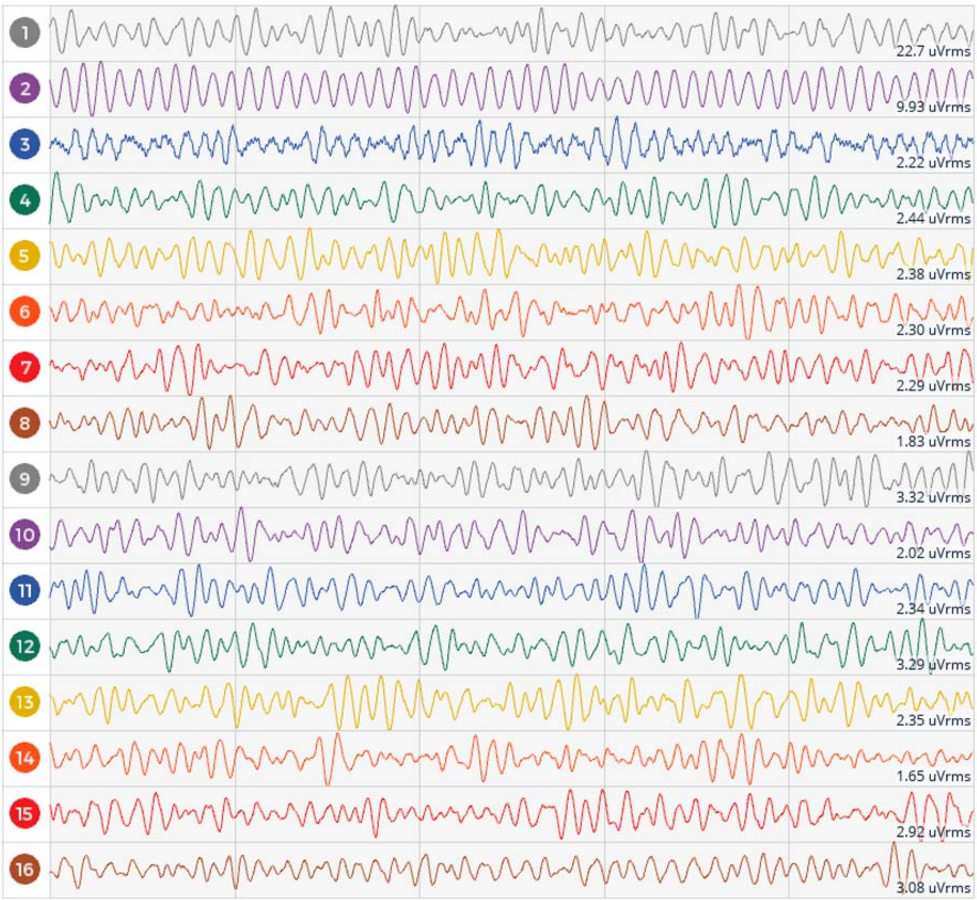


Figure 1.14. EEG Data with 45 FPS Sampling Rate

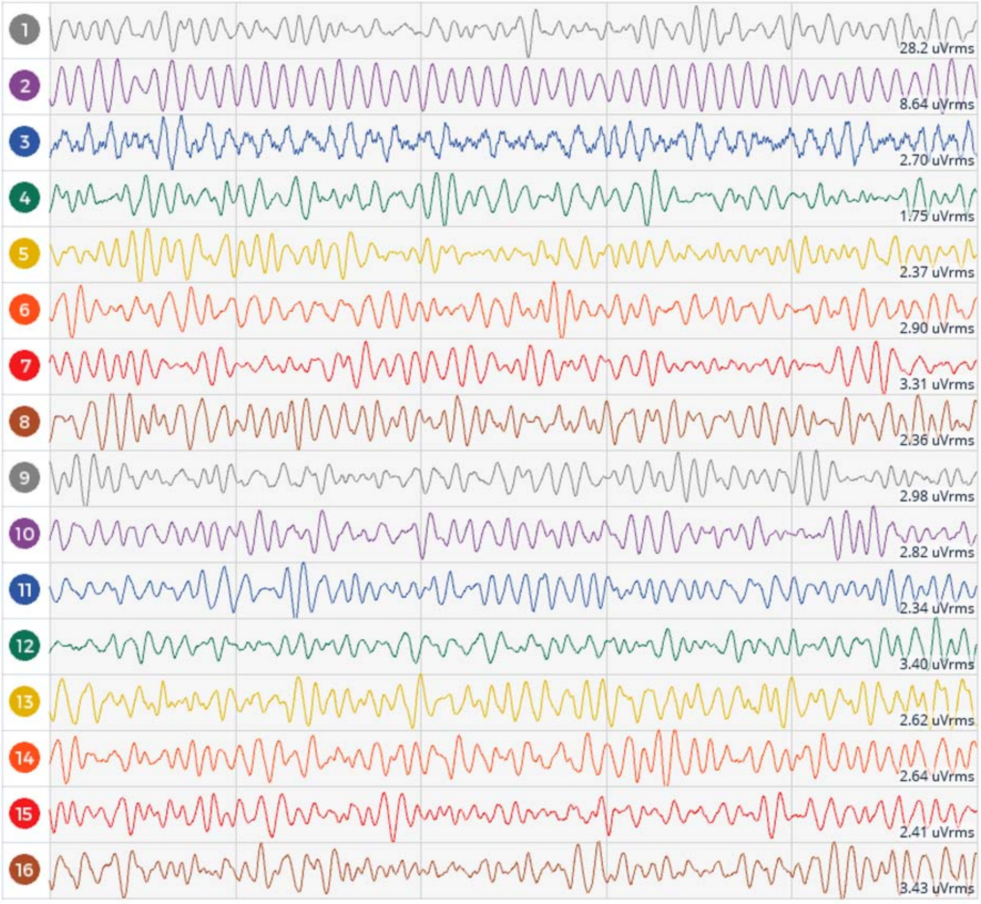


Figure 1.15. EEG Data with 60 FPS Sampling Rate

Developing a filter which is going to discard either the slow or the fast activity from a large set of numbers which constitutes the waveform is a distinct problem from designing RC circuits. An analog signal can go through an RC circuit, but discrete numbers cannot. We need some mathematical methods to work on digitized information for omitting different signal activities.

1.4.7.1. Digital HFFs

We focus on an algorithm to filter a fast signal from this digital waveform. The technique considered is alike to the technique which is called "moving averages". (This is also used to track stock prices) In this technique, a number is transformed by taking the average of the numbers before that number. The 101th number is replaced by the average of numbers before it and this goes on like this for the remaining numbers. The fast constituent of the wave is tremendously reduced, however it is discernible. The most noticeable feature of the wave is its slow component.

1.4.7.2. Digital LFFs

To filter out slow activity, successive bins are subtracted and original values are changed for the difference. The nth point is replaced by the difference between the nth and the (n-1)th value.

Actual digital filtering algorithms are way more complex than those considered above which have some defects. The reason why those examples are presented is to warn the reader that the techniques used in filtering is not alike to the features of analog circuits. Digital filters imitate RC circuits they replace. According to algorithms they use, digital filters have intrinsic problems.

1.5. P300 Speller

(Cuntai Guan, Thulasidas and Jiankang Wu, 2005)P300 speller is a means of communication by which texts or commands that can be input into a computer by thought. The probability of infrequent or task-related stimulus is in inverse proportion to the amplitude of the P300 evoked potential. In present P300 spellers, rows and columns of a matrix are boosted consecutively and randomly which culminates in a stimulus frequency of 1/N where N is the number of rows or columns of the matrix.

P300 potential is among the most stable and well-understood potentials. It is created by a rather strange paradigm: an anticipant event brings about a measurable potential difference at the central or parietal sites of EEG measurements. This positive potential usually occurs about 300 milliseconds subsequent to the event.

(Salvaris and Sepulveda, 2009)In Farwell and Donchin's first proposed P300 speller (FD-Speller), a 6x6 cell matrix is displayed, and it accounts for 26 letters and a few commands. The rows and columns of the matrix were consecutively and randomly intensified in a way that when the right row or column with the target cell was stressed, a P300 signal is obtained. Donchin utilized a bootstrapping approach and further improved the information transfer rate. Meinicke is the first to report the data-driven method for P300 speller. At the time of publication, the highest rate of information transfer was attained by them. Xu achieved good results on employing ICA-based subspace projections for P300 speller. Brendan conducted research on the connection between accuracy and various size of speller matrix. In a more recent study, Mellinger showed that P300 speller could be utilized for amyotrophic lateral sclerosis (ALS) patients.

1.6. Artifical Neural Network

It has been observed that artificial neural networks produce different results if they are trained as a result of changing parameters and initial values. It has been noticed that in some cases, they have learned a form they cannot recognize in others. As a result, it has been found that it is possible to train more than one network to train the same problem and to form a common decision by bringing together the results. These systems called converged networks, provide higher performance results than each of the constituent networks. It is as important in the mechanism that enables joint decision making as well as the networks within the system in compound networks. Networks are considered independently of others when they are being trained and tested. All networks are brought together after being trained, and their performance confirmed. There is no obligation to select the networks used in the system from any model. What is important is that the networks in the unified system have been trained on the same problem, and the format of their output is common. The topologies of the networks in the combined network, the aggregation and activation functions they use, the number of intermediate layers, and the number of elements in each intermediate layer may be different. The number of input and output units must be equal. It is not possible for networks to influence each other and their decision-making. The decision-making mechanism combines the independent decisions of the incoming networks with an approach of unanimity and forms the decision of the composite system about the input presented to the networks. It is not necessary to use only artificial neural networks in developed combined systems. It is possible to include traditional methods in the system. If a traditional and intuitive method can be developed about the event learned by the network, it can be considered as a part of the system. In the experiments, it has been seen that the use of artificial neural networks together with the heuristic methods has an important contribution in improving the performance of the system.

1.6.1. Machine Learning

Machine Learning is a branch of artificial intelligence and aims to identify unknown samples by learning from known sample. There are different machine learning techniques available with their own advantages and disadvantages for use. Currently, Artificial Neural Network, Genetic Algorithm and Support Vector Machine are the most commonly used to classify EEG data

Various machine learning techniques are used to classify EEG data and some of them are successful but lacks in accuracy. However, the following machine learning techniques are considered in most of empirical studies:

- K-Nearest Neighbor (KNN)
- Regression Tree (RT)
- Bayesian Network (BNT)
- Support V ector Machine (SVM)
- Artificial Neural Networks (ANN)

1.6.1.1. K-Nearest Neighbor

K-Nearest Neighbor (KNN) is one of the most basic and simple classification techniques. KNN is usually considered when there is no or very little knowledge available for the distribution of data. It is a potential non-parametric classification technique which completely bypasses the problem of probability densities.

While classifying using KNN, X is assigned with a label of most frequently represented between K-nearest samples. This determines that labels on KNN are examined; voting has been carried out and a decision is made. KNN classification technique was developed for the need to carry out discriminant analysis while reliable parametric estimates of probability densities are either unknown or difficult to find out

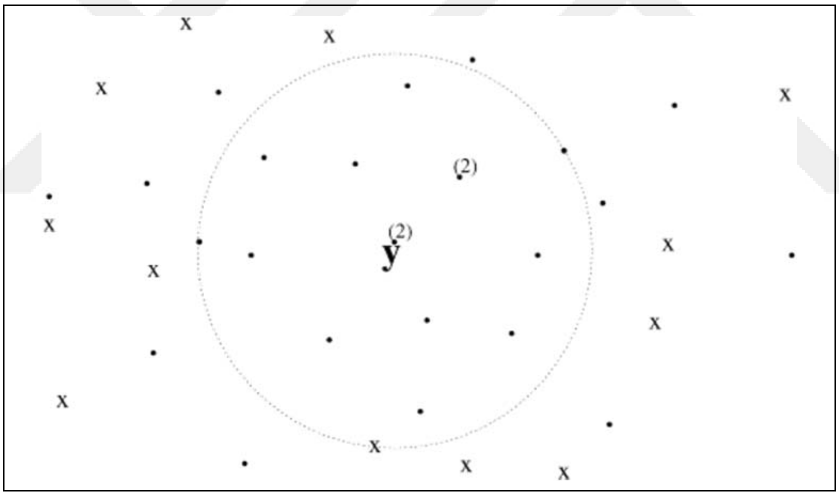


Figure 1.16. KNN

1.6.1.2. Regression Tree

Regression Tree (RT) takes an object or situation as input which is categorized a number of properties and provides a decision as an output. One input feature is represented by every node and possible test result values are represented by the branches of node. The positive test values can either be positive or negative.

If that node is reached, leaf nodes, also called as terminal nodes; represent the decision value.

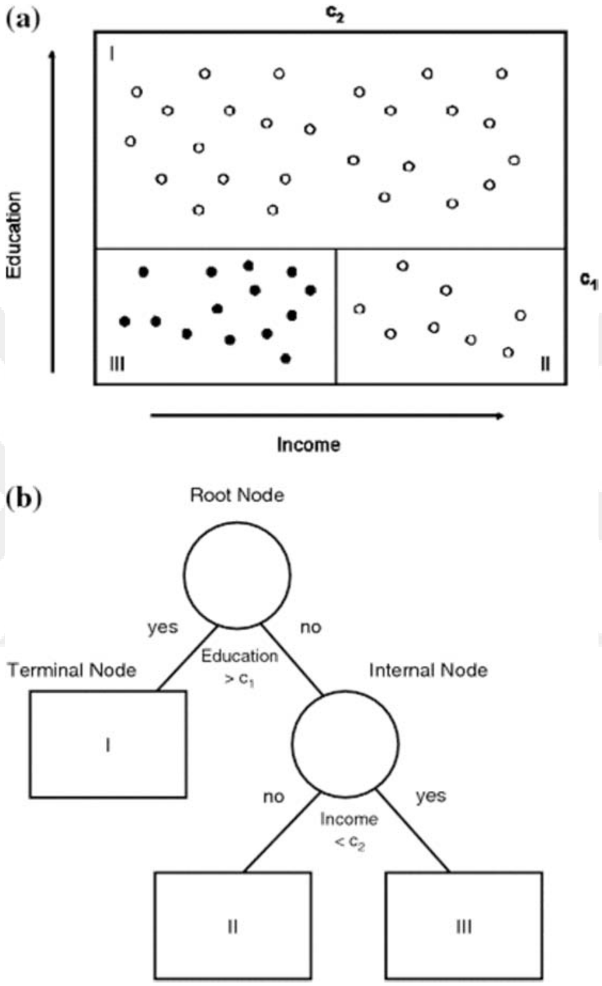


Figure 1.17. Regression Tree

1.6.1.3. Bayesian Network

Bayesian Network (BNT) is the most effective classifier in terms of predictive performance and state-of-the-art classifiers [35]. BNT is a graph that contains a network structure N which put a set of conditional independence relations between a set of variables C = {A_1, A_2 ... A_n} and a set of Tables T of local probability distributions associated with every variable. The joint probability distribution of A is determined by N and T. Network nodes have one- to-one contact with A variables. Therefore in N, single nodes are denoted by Ai whereas parent nodes are indicated by Pi.

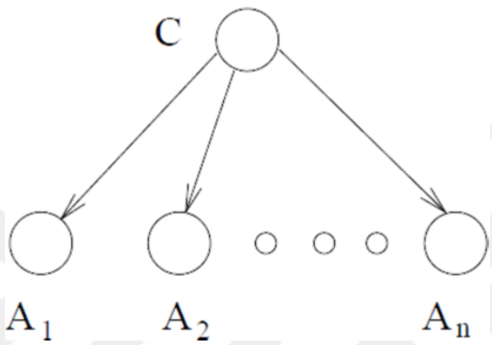


Figure 1.18. Bayesian Network

1.6.1.4. Support Vector Machine

Support Vector Machine (SVM) is a linear machine that operates in k-dimensional space created due to n-dimensional input data X into k-dimensional space using non-linear mapping φ(X). This helps to isolate data normally by geometry and linear algebra. To find a linear classifier for any data points with known class labels, it can be done by identifying a separating hyper plane.

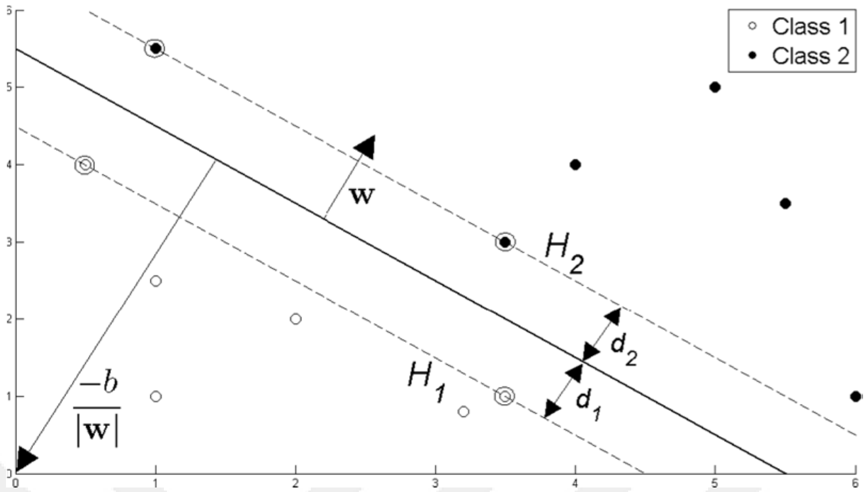


Figure 1.19. Support Vector Machine

1.7. EEG Devices

Most EEG devices are "non-invasive," which indicates that the electrodes which are utilized to observe the activity are placed on the scalp. Invasive electrodes that are operated within the matter of the brain or over the surface of the brain are sometimes practiced on people living with epilepsy to observe if the sufferer can have epilepsy surgery.

EEG is used in several different clinical contexts, such as diagnosing sleep disorders, coma, encephalopathies, and brain death, where the doctors generally concentrate on the spectral content of EEG, indicating the type of neural oscillations that are observed. These neural oscillations are generally simply termed "brain waves."

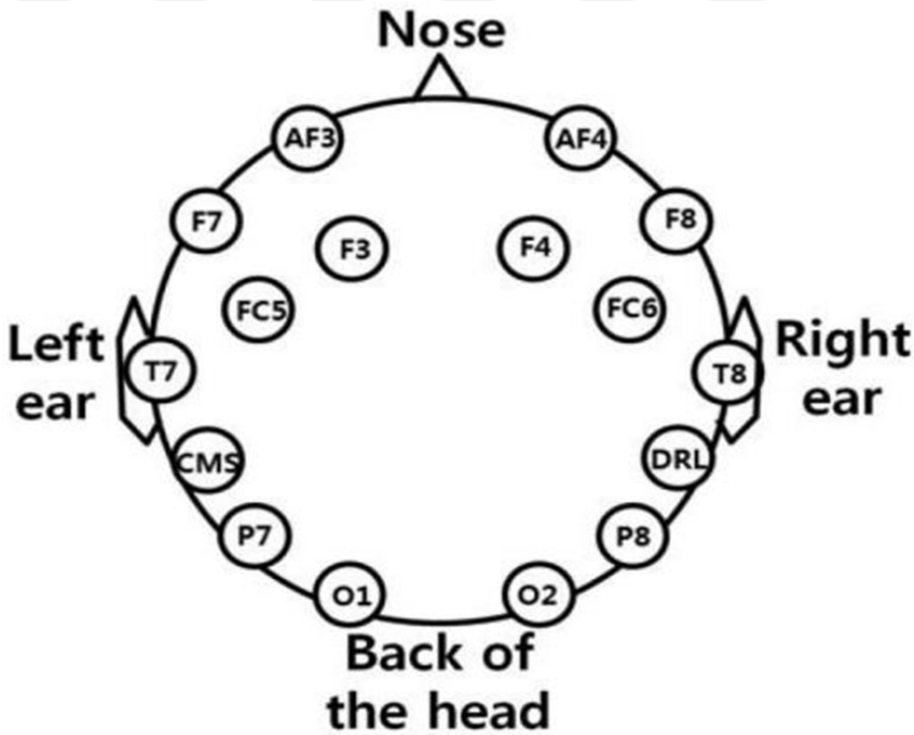
Techniques applied in cognitive science, cognitive psychology, and psychophysiological research frequently apply Even-related potentials (ERPs) that are averaged EEG responses, which are "time-locked" to more complicated processing of stimuli such as sensory, cognitive or motor events.

On Brain Computer Interface Field, there are many multiple low cost EEG Based Headsets exists.

1.7.1. Epoc Emotiv

The Emotiv EPOC and Emotiv Insight EEG headsets used in this project are both wireless and have the same capabilities for identifying "mental commands" using motor imagery according to Emotiv (Emotiv Inc, 2017).

The Emotiv EPOC has 14 electrodes placed in the positions AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1 and O2 using the standard 10-20 international EEG position system and two CMS/ DRL reference electrodes in the noise cancellation configuration placed on the left and right hemisphere of the head.



Bang JW, Choi JS, Park KR. (2017, May 14). The positions of 16 electrodes of the Emotiv EPOC headset.

Figure 1.20. Back of the Head

The electrodes require the saline solution to work, which is less untidy to use than conductive gel commonly used in medical-grade EEG headsets and takes less time to setup. For communication, you need a proprietary USB Bluetooth 4.1 dongle that enables the headset to transfer EEG data on the 2.4 GHz band to a computer. The headset records with a sampling frequency of 2048 Hz, which is reduced to 128 Hz before transmitting the data over Bluetooth. There are two versions of the Emotiv EPOC with different firmware where the "research edition" allows real-time raw data access, whereas the usual version does not.

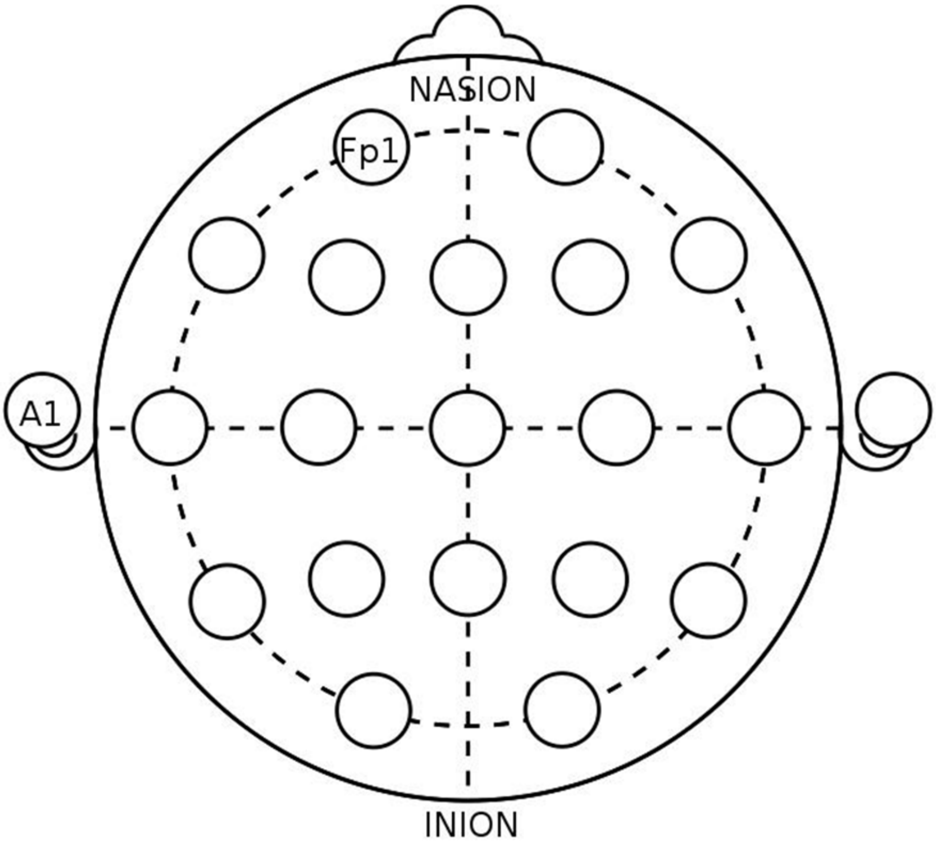
The Emotiv Insight has 5 electrodes placed in the positions AF3, AF4, T7, T8 and Pz using the standard 10-20 international EEG position system and two CMS/DRL reference electrodes in the noise cancellation configuration.

The electrodes do not require any saline solution in order to work, because they are composed of "long life semi-dry polymer" that makes a connection with the scalp using enclosing moisture. This makes it even less messy compared to both the Emotiv EPOC and medical-grade EEG headsets that use conductive gel and takes less time to setup. For communication, you need a proprietary USB Bluetooth 4.1 dongle that enables the headset to send EEG data on the 2.4 GHz band to a computer. The headset records with a sampling frequency of 128 Hz that is sent to the computer over Bluetooth.

NeuroSky MindWave

The NeuroSky MindWave (NeuroSky, 2017) is a consumer-grade EEG headset with one electrode placed in the position FP1 using the standard 10-20 global EEG position system and three reference electrodes nearby the left ear.

The MindSet uses the patented eSense algorithm (NeuroSky Developer, 2014) to interpret the mental events of attention and meditation of the user. By monitoring the level of stamina in alpha, beta, and theta frequencies, the headset can use brain state values to command computer applications using commands.



https://en.wikipedia.org/wiki/10-20_system_(EEG)#/media/File:21_electrodes_of_International_10-20_system_for_EEG.svg

Figure 1.21. International 10-20 Electrode System

The electrodes does not need any saline solution in order to work, because they are dry passive electrodes that makes contact with the scalp using surrounding moisture. The headset uses a Bluetooth to communicate with a computer.

2. PREVIOUS WORKS

(Salvaris and Sepulveda, 2009) Farwell and Donchin are the first P300 spellers. They used a 36-character visual stimulus display. The focuses on the letter he wants to transmit, and the computer detects the focused character in real-time. The computer performs detection by taking advantage of the P300 response generated by the user each time the row or column of the focused letter is burned. In the second stage, the system was analyzed by using the information recorded in the training stage. As a result of their analysis, they reported that the system they created could provide communication at a speed of characters per minute.

(Allison and Pineda, 2003) Allison and Pineda studied the impact of the letter matrix size used on the visual stimulus screen on the P300 speller. They emphasized the effect of matrix size on EEG measurements, target detection success, and user preferences. The smaller the matrix size, the shorter the P300 delay time. In smaller matrices, the P300 was formed earlier than in the larger matrices. The matrix size did not make a significant difference in target detection success. Users have not made a choice about the size of the small or large matrix; most of the characters in the edges and corners can be counted easier.

(Nijboer *et al.*, 2008)Birbaumer made a study on the current status of brain-computer interfaces. He described interventional BCI's that are usually implanted in the brains of animals and noninterventional BCIs that perform electrophysiological recordings from humans. Non-invasive BCI's for fully paralyzed or self-confined patients have been reported to provide slow crustal potentials, sensorimotor rhythm, and P300 communication in clinical practice. However, non-invasive BCI's have been reported to be unsuccessful in fully self-confined patients. On the other hand, it was observed in studies on interventional BCIs and healthy animals that reaching, grasping and forcing work could be done. Newly developed fMRI and NIRS-based BCI's has been shown to be promising for the regulation of neurological and emotional disorders in children.

(Fazel-Rezai *et al.*, 2012)Sellers and his team determined the characteristics of the P300 spellers have made a study. Spellers use a visual stimulus matrix of letters and numbers. The user focuses on the character he wishes to transmit, followed by the burning of the row and column where the character is located. In the study, two different matrix sizes, 3x3 and 6x6, were used for the visual stimulus screen.

In addition, two different periods, 175 ms and 350 ms, were used for combustion and extinguishing.

For a period of 175 milliseconds, the duration of burning a row or column is 100 ms, and the duration of the matrix is 75 ms. For the 350-millisecond period, a 200 ms burn-in and 150 ms off time were determined. The real time performance rate was highest for a 3x3 matrix size and 175 ms period. The highest transmission rate was 6x6 matrix size and 175 ms period. For the best case, the average speller usage success rate of all subjects was 88%. The amplitude of the P300 response was significantly higher than the 3x3 matrix for the 6x6 matrix. As a result of the study, it is stated that matrix size and period are important variables to consider for P300 speller optimization.

(Nijboer *et al.*, 2008)Krusienski reported that the extension of the classic P300 attribute space, studied the effects of the classification of data collected from the P300 spellers. It is stated that the classifier created using Stepwise Linear Discriminant Analysis (LDA) is compared for the general purpose of the P300 classifiers, not only for the effects of spatial channel selection, channel relationship, data subsampling, and maximum model attribute number. It has been reported that an increase in the online performance of the P300 speller is observed and useful offline parameters are obtained by adding additional recording zones to the classic P300 recording zones and using LDA as a classifier.

(Nijboer *et al.*, 2008)Nijboer and his team evaluated the efficiency of P300 syllable in patients with Amyotrophic Lateral Sclerosis. In the P300 syllable, Stepwise Linear Discriminant Analysis (LDA) is used as a classifier. Each character selected as a result of classification is shown as feedback to the user. In the first phase of the study, six users used a speller operating at a rate of 1.2 selection/minute with a 6x6 visual stimulus matrix for 12 separate days: 62% online and 82% offline average accuracy. In the second phase, four users achieved an average online rate of 2.1 9 selection/minute and an average accuracy of 79% using new and instant expressions using a visual stimulus matrix of 6x6 or 7x7 size. P300 amplitude and latency were observed to remain stable even after 40 weeks. It was concluded that patients could communicate with the P300 speller, and performance would be stable in weeks.

(Fazel-Rezai *et al.*, 2012)Fazel-Rezai and Abhari (2009) created a P300 speller using a regional-based visual stimulus display. In their studies, it was shown that human perceptual errors occurred when using the P300 speller developed by Farwell and Donchin. They reported that when periods of less than 500 milliseconds are used, people perceive the first combustion but not the next combustion. The other human perceptual error is shown to be able to react to the adjacent neighboring rows and columns, except for the rows and columns where the letter is focused. In order to eliminate these errors, they developed a visual stimulus based on the principle of zone burning instead of burning row by column. The stimulus works in 2 stages. In the first stage, the visual stimulus matrix containing seven regions consisting of 7 characters is shown to the user. The user focuses on the region of the character he wants to transmit.

The seller determines the region of focus by classification. Next, only seven characters in the focused area are displayed. In this screen, the user focuses on the letter he wants to transmit, and the system detects the character. They reported that the error rate of 36.7% in the system developed by Farwell-Donchin decreased to 18.3% in the newly developed system.

Guger and his working group has been reported that there are three main factors that affect the strength of the visual stimulus. High accuracy system timing, video graphics display technology, and process priority management have been expressed. In their measurements, the system timer used in a dedicated process showed a high accuracy performance with a delay of fewer than 300 microseconds. As a result of the random placement, uncertainty increased, and therefore P300 amplitude was reported to increase.

Blankertz prepared a training on the analysis and classification of event-related potentials in a single trial. Analysis of event-related potentials (ERP) in a single trial; They stated that it was quite complicated because of the high variability among the trials and the high signal to noise ratio. The training includes a comprehensive study on the analysis of ERPs, elaboration of linear methods and space-time patterns and filters for linear ERP classification. However, it is stated that these techniques require accurate estimation of the covariance matrix in high dimensional sensing space and form a narrow pass. They proposed to use estimators as a solution and showed that the regulation of linear decomposition analysis using estimators yielded much better results for the classification of ERP in a single trial than classical linear decomposition analysis. They also gave practical clues as to which classifiers were learned from the data and demonstrated the trade-off between layout accuracy and model complexity for the regulated LDA.

Taha reported that, in order to reduce the number of stimulus repetition and increase the speed of the data transfer system, they have made changes to the interface and classification system of the P300 spellers. They incorporated a dictionary of their own into the classification systems and collected 15-word copy spelling data from 14 healthy subjects. Following the addition of the dictionary to the system, they achieved a percentage increase from 72.86% to 95.7% in the success rate of the post-trial analysis. Based on the hypothesis they have confirmed, they have only changed the position of the letters in the matrix on the classical visual stimulus screen. They spelled the same words to the same subjects and observed that the data transfer rate reached 55.32 bits/minute in the second attempt.

Pires (2012) developed a P300-based BCI with a new letter layout called Novel Lateral Single Character (NLSC). They compared this new layout with the classical 11Line / Column layout. They argued that the NLSC they prepared shortened the character selection time by using an event strategy to cover all characters in the alphabet with a single character type. In addition, they aimed to comprehend the real hemispherical asymmetries in the visual perspective to increase BCI performance. Row/Column and NLSC were tested on ten subjects. 7 of the subjects had ALS, five had Cerebral Parsi 1 (SP1), had Duchchenne Musküler Distrofi (DMD) and 1 had Spinal Cord Injury (SCI). As a result, the signal/noise ratio obtained with the NLSC was higher than that of the Row/Column placement.

Quadimato and his friends claimed that efficiency meter ”describes how the BCI assessment measure is used for BCI and how the performance assessment is performed. They stated that the efficiency measure also includes penalties and error-minimization strategies, unlike other BCI measures. Therefore, they stated that this measure better describes the behavior of BCI systems. They compared the efficiency meter with those described by Wolpaw and Nykopp in terms of accuracy and speed of information transmission. The results of their studies reported that the efficiency meter could predict whether communication with the BCI system is possible. It has been claimed that the efficiency meter is a more general and versatile meter in the evaluation of BCI systems since it can be easily modified on the meter in order to evaluate different characteristics.

Muzaffer Doğan and his team worked on artificial neural network methods perceptron, self-regulating networks, and backpropagation algorithms were tried for the diagnosis of headache diseases. The levenberg-Marquardt algorithm is the fastest working algorithm among backpropagation algorithms. The levenberg-marquardt algorithm was found to be a preferable algorithm when compared to other backpropagation algorithms, although an average of 3,5 samples out of 19 test samples were misdiagnosed. However, even the most efficient of the backpropagation algorithms failed to provide the speed and reliability of perceptron. Although Perspteron is the simplest artificial neural network model, it has been very effective in diagnosing headache diseases. This is thought to have a large share of the fact that the space of symptoms is linearly separable. Self-regulating networks, on the other hand, provided success and speed close to perseptron.

3. MATERIALS AND METHODS

(Chiesi *et al.*, 2019) OpenBCI is an open-source platform and a circuit board especially developed for EEG, Electromyography (EMG) and Electrocardiography (ECG) applications (OpenBCI , 2017). The OpenBCI board can be obtained separately and you can use a do-it-yourself headset with it (Russomanno, 2017). You can position the electrodes elsewhere on the scalp . In deciding the headset for the project, The Mark III Nova iteration of the 3d-printed headset frame was considered and it has the following electrode positions: Fp1, Fp2, C3, C4, P7, P8, O1 and O2 which are the standard 10-20 international EEG position system.

The OpenBCI 8-channel version (OpenBCI, 2017) has been utilized successfully in a P300 speller system with the following electrode positions: C3, Cz, C4, P3, Pz, P4, O1, O2 and with custom settings (Frey J. , 2015).

Another application of the OpenBCI is controlling video games through motor imagery with the electrodes positioned at C3, Cz, C4, FCz, Pz, CPz, O1, O2, C5, FC3, CP3, C1, C2, FC4, CP4, C6 (Frey J. , 2015) by means of OpenVibe (OpenVibe, 2017) software platform.

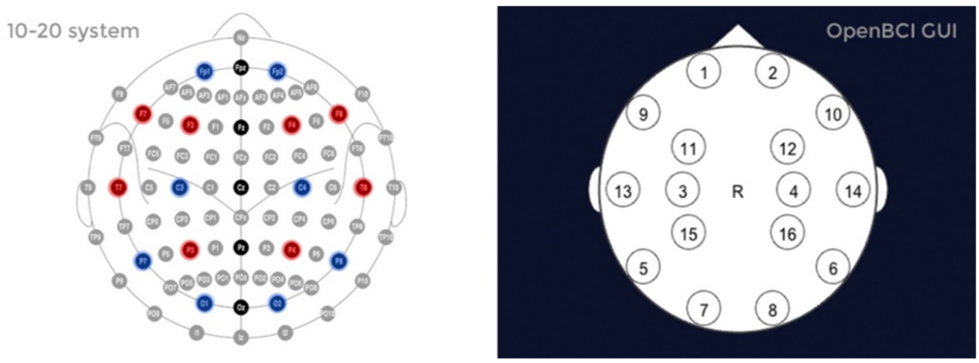
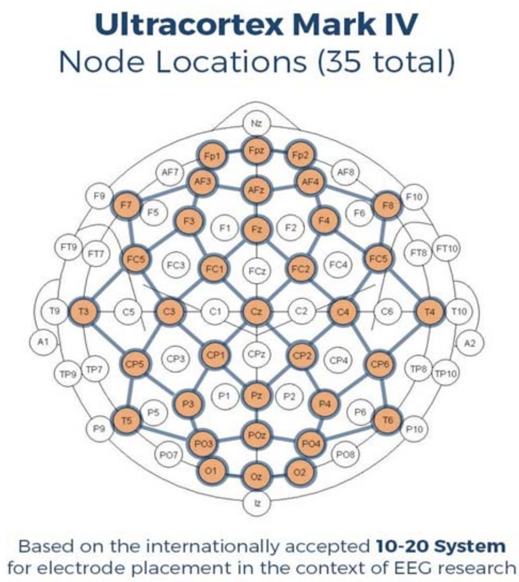


Figure 3.1. OpenBCI Head Headset

Figure OpenBCI. (Photographer). (2017, May 14). Picture of the positions of the electrodes for the OpenBCI headset. Retrieved from https://github.com/OpenBCI/Ultracortex/tree/master/Mark_III_Nova_REVISED

(Tada *et al.*, 2019)The most recent and the far best iteration of the OpenBCI 3d-printed headset frame is the Ultracortex Mark IV (OpenBCI, 2017) which uses 35 electrodes in the positions Fp1, Fpz, Fp2, AF2, AFz, AF4, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC5, T3, C4, Cz, C4, T4, CP5, CP1, CP2, CP6, T5, P3, Pz, P4, T6, PO3, POz, PO4, O1, Oz and O2.

In the product description there is a disclaimer saying that the headset is: “not a medical device nor is it intended for medical diagnosis and provided to you "as is” (OpenBCI, 2017).

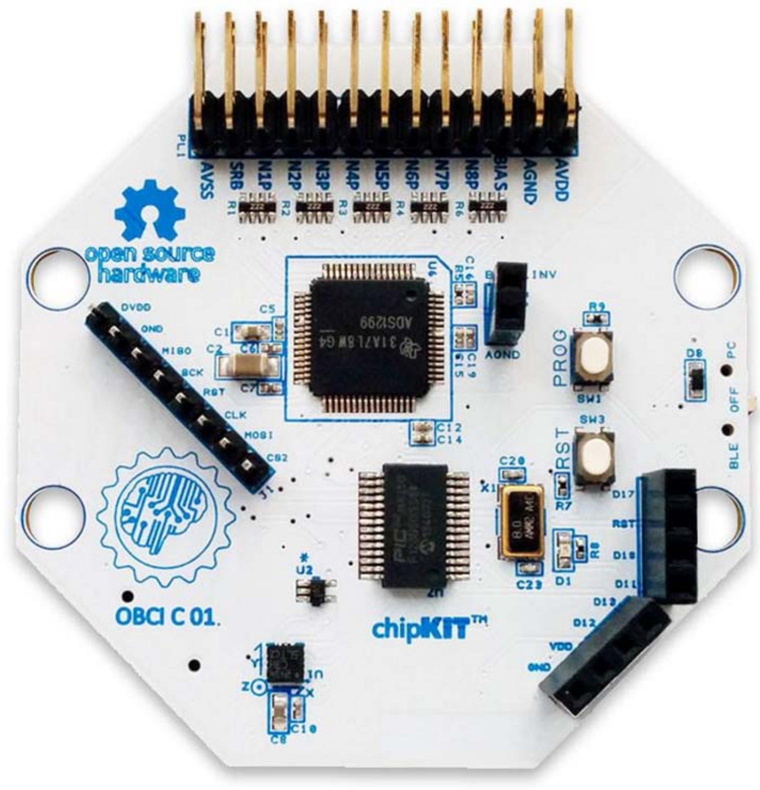


OpenBCI (2017, May 14). Picture of the positions of the electrodes for the Ultracortex "Mark IV" EEG Headset. Retrieved from https://shop.openbci.com/products/ultracortex-mark-iv

Figure 3.2. 10-20 Electrode Placement in Context of EEG Research

The Cyton OpenBCI Board is a 32-bit processor that comes with an 8-channel neural interface and is also Ardunio-compatible. The PIC32MX250F128B microcontroller implemented by Cyton OpenBCI Board provides the device with considerable amount of local memory and processing speed. The board comes with the chipKIT™ bootloader and is pre-flashed. Besides it has the most recent OpenBCI firmware.

The OpenBCI Cyton Board and OpenBCI Daisy Module (which fits into the OpenBCI Cyton Board) are capable of reaching 16 channels of brain activity (EEG), muscle activity (EMG), and heart activity (ECG) for sampling. The system is in communication with a computer through the OpenBCI USB dongle through RFDuino radio modules. It has also the ability to connect to however mobile device or tablet as long as those are in compatibility with Bluetooth Low Energy (BLE).). Data sampling rate of The CytonDaisy Board is at the speed of 125 Hz on every ne of its 16 channels.



OpenBCI (2017, May 14). Picture of Cyton and Daisy Biosensing Boards Retrieved from https://shop.openbci.com/collections/openbci-products/products/cyton-daisy-biosensing-boards-16-channel?variant=38959256526
Figure 3.3. Cyton and and Biosensing Boards

EEG signals are classified as rhythmic and transient and are complex signals in nature as shown in figure below. The rhythmic activity is distributed into different frequency bands. People of different ages may emit different amplitudes and frequencies of EEG signals while they are performing a task or relaxing.

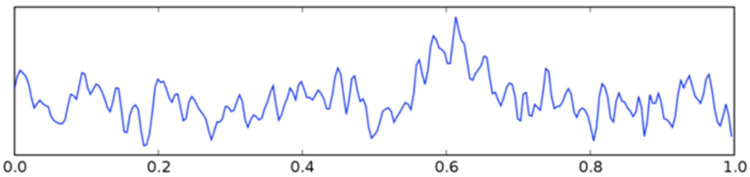


Figure 3.4. EEG Waves

According to frequency ranges, five wave types can be established. With alpha (α) being the least frequent and the gamma (γ) being the most frequent, theta (θ), beta, (β), and delta (δ) are placed in between with an order of increasing frequency.

A unique wave is mostly found in a particular lobe of the cerebral cortex; however, this is not always the case. Various mental events are related to various waves which are essential to determine one's position at a specific time.

Wave Name	**Rate of Frequency (Hz)**	**Mental Condition (State)**
Delta (δ)	Between 0 and 4	Deep Sleep
Theta (θ)	Between 4 and 8	Creativity, Drifting Thoughts, Dreams
Alpha (α)	Between 8 and 13	Abstract Thinking ,Calmness, Relaxation,
Beta (β)	Between 13 and 30	Highly Alertness, Highly Focused
Gamma (γ)	More than 30	Multi-Tasking ,Simultaneous Process

For example, Delta waves are beneath the frequency scale of 0 – 4 Hz. Mental events pertaining to these waves are deep sleep, unconsciousness or anesthesia, and seldom awake. If one generates a Delta wave when he or she is awake, then this is considered an unhealthy situation. The higher the amplitude; the more serious the problem is. These waves have low amplitude in healthy bodies when they are awake.

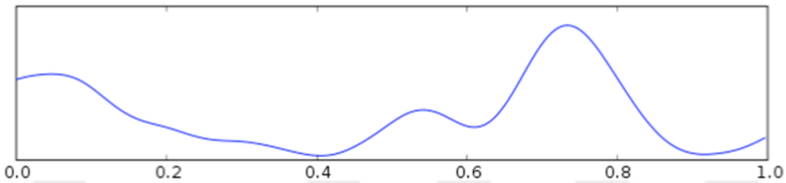


Figure 3.5. Delta Waves

Theta waves are beneath the frequency scale of 4 – 8 Hz. Mental states associated with these waves are floating thoughts, creative thinking, and unconscious substances. These waves are found in central, temporal, and parietal parts of head. A healthy body in deep sleep emits Theta waves.

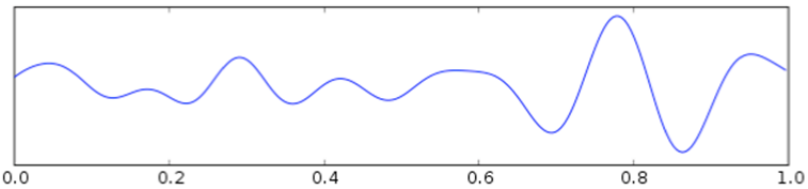


Figure 3.6. Theta Waves

Alpha waves are beneath the frequency scale of 8 – 13 Hz. Mental states related to these waves are relaxed and calm events. These waves are generated on the backside of the head and occipital area of the brain. These waves are of higher amplitude than those of others. Alpha waves can be identified if the subject is calm and conscious. These waves can interfere with μ-rhythm at times. A calm, awake and healthy body gives out Alpha waves.

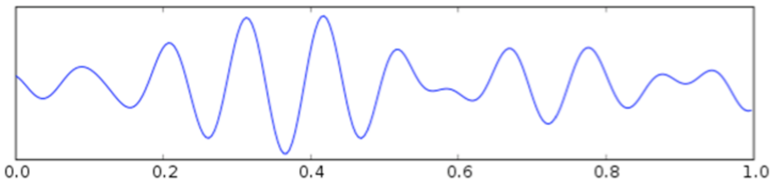


Figure 3.7. Alpha Waves

Beta waves are beneath the frequency scale of 13 – 30 Hz. Mental states pertaining to these waves are being highly focused and alert, such as being in the state of deep thinking and attention. Beta waves have a wide band of frequency compared to other waves. These waves stem from the front side of the head and the centeral area of the brain.

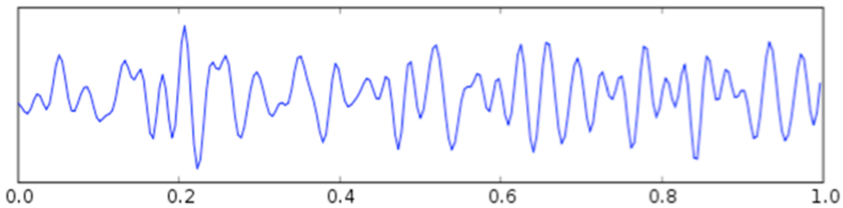


Figure 3.8. Beta

Gamma waves are beneath the frequency scale of 30 Hz. Mental events associated to those are synchronous activity and multi-tasking. These waves are hard to detect due to their very low amplitude. These waves appear at every part of the brain.

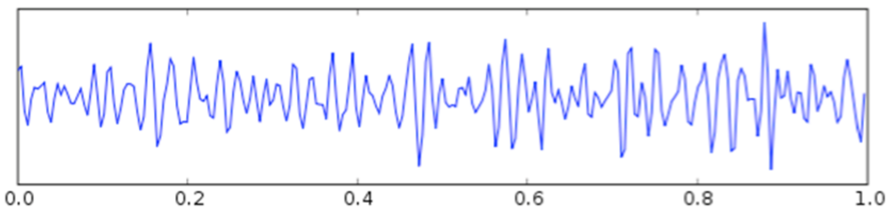


Figure 3.9. Gamma

EEG signals are retrieved from the scalp by means of electrodes connected to human head. The main principle of EEG is that the potential difference between two electrodes are calculated. One or more electrodes are connected either to mastoids or ear lobes. These are reference electrodes and they are used to find the background electric field of the scalp. The position of reference electrodes are important, they shold not be placed so close to head and any other part of the body as the electrical activity of fibres or heart is likely to interfere with these electrodes' job.

Other EEG devices are offered for use equipped with a certain number of electrodes and filters. Those tools acquire analog EEG signals and these signals are subsequently transformed to digital data. Artifacts are excluded on the way by filters. Unnecessary frequencies such as Electromyography (EMG) and Electrocardiography (EKG) are discarded by means of low pass and high pass filters. Analyzing data in the course of data processing is also important. Sampling frequency, sampling rate and a portion of electrodes are all play crucial roles in the process of recording EEG signals.

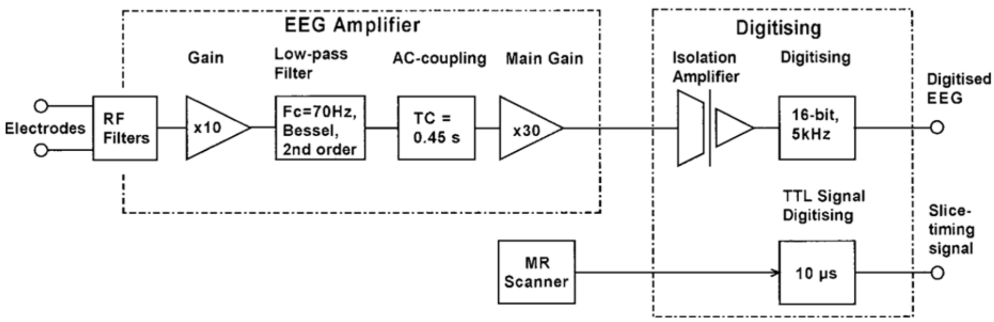


Figure 3.10. EEG Amplifier - Digitiser

Artificial neural networks, by training, imitate the neurons of human brain when brain is in the process of learning something and identifying patterns. This chapter provides an introduction to this topic, fundamental terminologies, and constituents of ANNs.

Artificial neural networks are models of computational structure copying the function of human brain. ANN’s can solve complex problems like function approximation, classification, and pattern recognition and with this feature it stands out from other analytical tools. What is more, it is an optimization tool for complex and non-linear problems. An ANN is comprised of many layered neurons that are connected to one another to constitue an inter-dependent network. Neuron is the smllest particle of a neural network. According to Dreyfus, a neuron is a “nonlinear, parameterized, bounded function.” Figure 3.11 depicts a simple neuron.

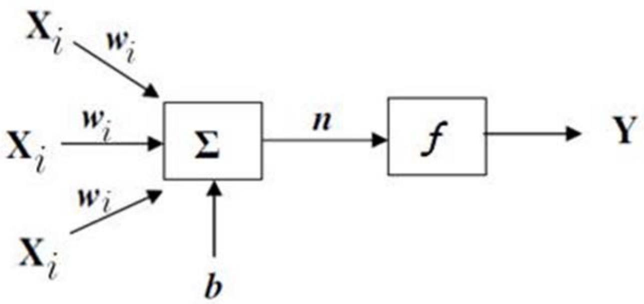


Figure 3.11. Simple Neuron

A neuron has multiple inputs and outputs; the output of a neuron is the culmination of a non-linear combination of the combination of the inputs { X_i}, multiplied by the factors which are called the synaptic weights { w_i}, and a function { f } that is applied on the result. Every neuron has an associated weight which reflects the effect of the signal it generates. Weights are determined with respect to prior experience acquired in the course of training. After weight functions are determined, subsequent processing is carried out with the activation function {f}. Among the inputs to a neuron is a bias {b} whose numerical value is 1. It is sometimes denoted as.

An activation function, also known as transfer function, is a function maps the weighted sum of the inputs and the bias and is written as:

$$\boldsymbol{y = mx + b} \tag{3.1}$$

The function can be of linear or non-linear nature, among those functions are pure- linear, sigmoid, hyperbolic, and Gaussian. Figure 3.12 depicts some of the most utilized functions.

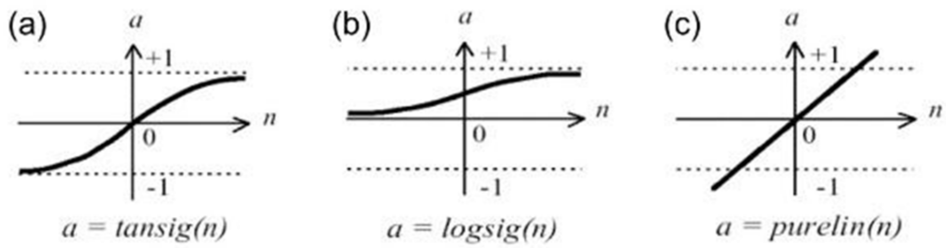


Figure 3.12. Activation Functions

Neurons are the basic building blocks all networks and without exception work in the way explained above. Neurons are positioned in a layered arrangement and connected that way so data can pass from one layer to other. The first layer is called an input layer and the last one is called an output layer. Feed-forward neural networks and recurrent (feedback) neural networks are two types of neural networks. Both were used in the research and are considered in the next section.

Feed-forward neural networks are the most common among other ANN's due to their ease of use. The information travels through the input layer, one or multiple hidden layers and finally the output layer.

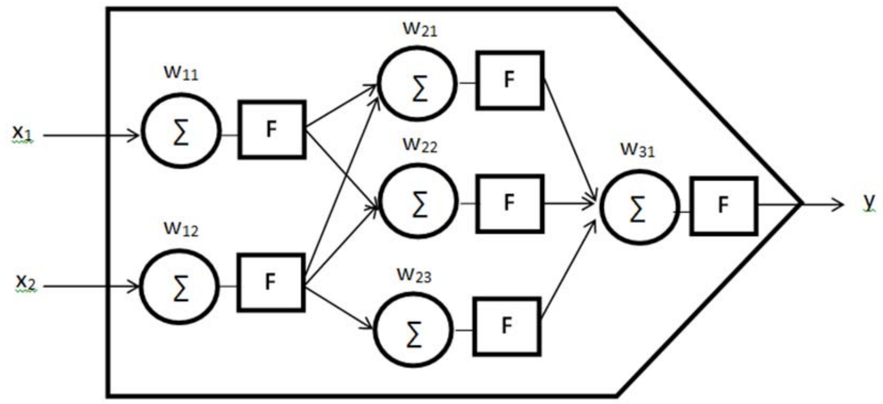


Figure 3.13. Feedforward Neural Network

For a network with 1 hidden layer, if we denote as the input layer, as the hidden layer, and as the output layer, the input is propagated through the hidden layer such as

$$\boldsymbol{y_j(t) = f(net_j(t))} \tag{3.2}$$

$$\boldsymbol{net_j(t) = \textstyle\sum_i^n x_i(t) w_{ji} + b_j} \tag{3.3}$$

Where the output function for the jth hidden layer node for time t is denoted as $y_j(t)$, the

number of inputs is denoted as n, the weight connecting the jth hidden node and the ith input node is denoted as w_{ji}, and the bias of the hidden layer is denoted as b_j. That function will then spread to the output layer:

$$\boldsymbol{k(t) = g(net_k(t))} \tag{3.4}$$

$$\boldsymbol{net_k(t) = \textstyle\sum_j^n y_i(t) w_{kj} + b_k} \tag{3.5}$$

Where is the output function of the kth output node for time, hidden neurons, the weight connecting the kth output node is denoted as w_{kj}, and the bias of the output layer is denoted as b_k.

Simplicity of Feed Forward Neural Network makes it a popular choice. When the network is intialized, random assigned weights can later be altered to make the error of the output as small as possible. No method other than supervised method is considered in this research. In supervised method, a network is trained through examples and those examples can be compared with the output of the process. Every input has an equivalent output. The network error is defined as the difference between the correct output and the estimated output. The network tries to minimize that error. The training algorithm generally used with FFNN is the error back-propagation algorithm. That algorithm works this way: With constant weights, the input signal flows through the network forwards, then the error goes back from the output layer to the input layer. Finally the weights are arranged according to the error-correction rule.

The common learning algorithm used for ANNs is the back-propagation algorithm. A number of forms of this algorithm exist. The simplest one is where the error function is reduced the fastest (negative gradient) to alter weights and biases. A single iteration of the process is written as

$$\boldsymbol{x_{k+1} = x_k - \alpha_k g_k} \tag{3.6}$$

Where the vector of weights and biases is denoted as x_{k+1}, the learning rate is denoted as α_k, and the gradient is denoted as g_k. Generally the back-propagation algorithm seeks the minimum value of the error function through following its gradient. For the sake of computation, the function should be differentiable and continuous, and to make sure this is the case a proper activation function should be picked.

The solution of a neural network problem is the correct picking of weights to generate the minimum error. The weights are given values randomly, then gradient of the error function is determined and this is used to adjust the starting weights. Those steps are carried out recursively until arriving at an error that cannot be further decreased. This final error is a minimum.

The most frequently used error function is the mean square error (MSE), which is written as:

$$\boldsymbol{MSR} = \sum_{i=1}^{n} \frac{1}{n} (\boldsymbol{O} - \boldsymbol{T})^2 \quad (3.7)$$

where the output of the neural network is denoted as O and the target valueis denoted as T. Figure 3.14 illustrates how this error function is computed for one neuron; all computed values are added subsequently.

Although the back-propagation is usually used with FFNN networks, its utilization can be carried over into recurrent networks including NARX networks

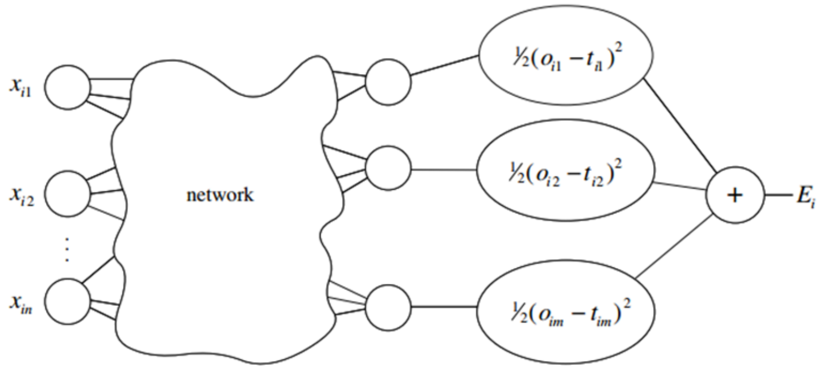


Figure 3.14. Back-Propagation Network

The back-propagation algorithm is in use with success in many real engineering applications, it has two main disadvantages: slow learning speed and being sensitive to parameters. Several modifications to the algorithm were developed which deals with the negative features while reaping the positive ones. Those developments created the following: Gradient descent back-propagation with adaptive learning rate and momentum coefficient, Quansi-Newton, resilent back-propagation, and Levenberg-Marquardt algorithm.

Levenberg-Marquardt algorithm is better than simple gradient descent and generally performs well. It certainly is one of the most utilized algorithms. MathWorks has tested nine commonly used back-propagation algorithms and came to the conclusion that Levenberg-Marquardt has the most rapid convergence and has the lowest mean square error if a function approximation problem is considered on a small to medium network. What is more, that algorithm is the best choice for pattern recognition problems.

Levenberg-Marquardt algorithm is a compromise between the simple gradient-descent and Newton‟s method. While the simple gradient descent exhibits a number of convergence problems, Newton‟s method make up for these problems through the use of second derivatives

The Newton method is expressed as:

$$\boldsymbol{x_{k+1} = x_k - H^{-1} g_k} \tag{3.8}$$

Where the training step is denoted as x, the Hessian matrix is denoted as H, and the gradient is denoted as g. The Newton method converges rapidly but the computation of Hessian matrix is very costly. Levenberg-Marquardt enjoys benefits of both gradient-descent and Newton's method. It has a second order convergence and works without resort to calculating the Hessian matrix.

Therefore, the Hessian matrix can be approximated as:

$$\boldsymbol{H = J^T J} \tag{3.9}$$

and the gradient as

$$\boldsymbol{g_k} = \boldsymbol{J^T e} \tag{3.10}$$

Where the Jacobian matrix (first derivatives of network errors) is denoted as J and the vector of network errors is denoted as e. Calculating the Jacobian matrix is a lot easier than computing the Hessian matrix. Therefore, the Levenberg-Marquardt iteration is written as:

$$\boldsymbol{x_{k+1}} = \boldsymbol{x_k} - [\boldsymbol{H} + \boldsymbol{\mu I}]^{-1}\boldsymbol{g_k} \tag{3.11}$$

As the learning rate μ approaching zero the algorithm becomes the Newton and when μ increases it turns out to be the gradient descent with small steps. Because the Newton method bears a fast convergence feature the algorithm has a tendency to go towards it as quick as possible. This means μ becomes lower after every single iteration provided that the performance function keeps getting smaller to lower the effect of gradient-descent. If the performance function gets higher, the value of μ goes up again to pursue the gradient further.

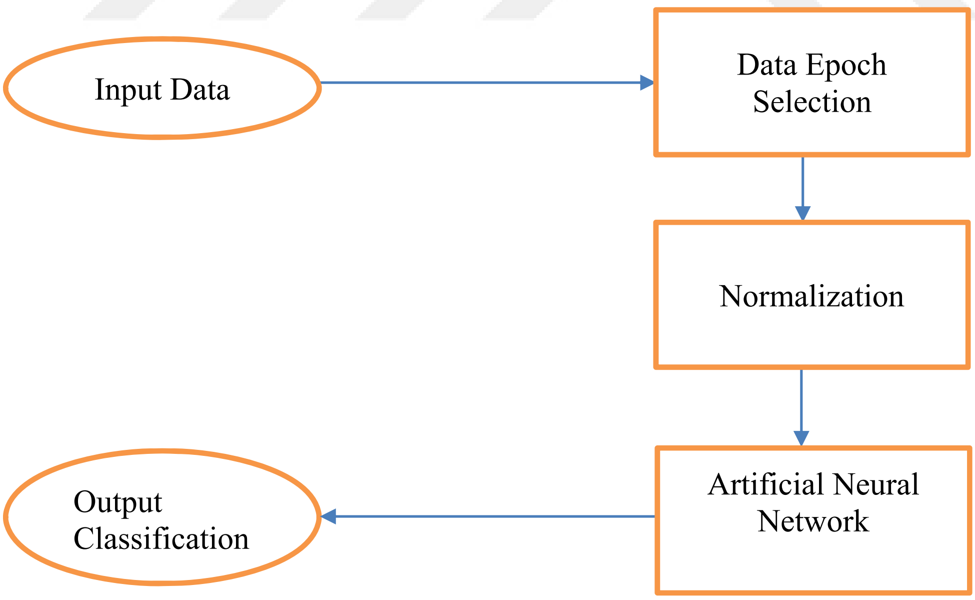
4. EEG UTILIZED TEXT SYNTHESIS SOFTWARE

Software Development Life Cycle of Text Synthesis for EEG Signals

During this application development, basicly there is certain flows are followed in below.

- Data Collection via OpenBCI Headset and using Pygame Libraries
- Data Preprocessing through OpenBCI, Numpy, Panda, Scipy and self developed libraries
- Training Period of Data to determine proper Artificial Neural Network for Predictions
- Testing Data

Here is the main flow of SDLC in this progress



For gathering input data, Open BCI headset, Pygame Library has been used. OpenBCI allows user to capture their incoming EEG signals immediately. To create proper dataset via Pygame library, 9X4 Matrix includes all English letters and 0-9 digits were drawn.

For each letter starting from A to Z, by 600 FPS, each letter is shown to user. Until A is being pictured, 9 different letters has showed to user before achiving proper letter. Below is the sample of capturing letters and digits.

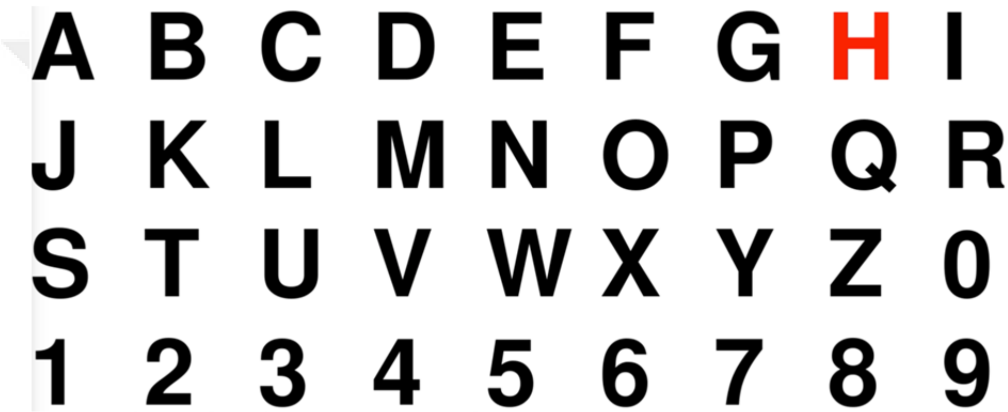


Figure 4.1. Letters and Digits

After data is being captured for each letters and digits data is being filtered with high pass and averaged as 1000 sample. Before training period of data, min/max normalization has been done.

After data is being filtered and normalized, %80 of data is separated for training %20 percent of data was holded for test. Before training the network, dataset randomly shuffled.

Artificial Neural Network for training and testing consists of 16 Input, 2 X 10 Hidden Layer and 36 Output. As activiation functionals, Rectifier and Softmax functions were used. In the figure below, it can be found architectural visualization of Artifical Neural Network

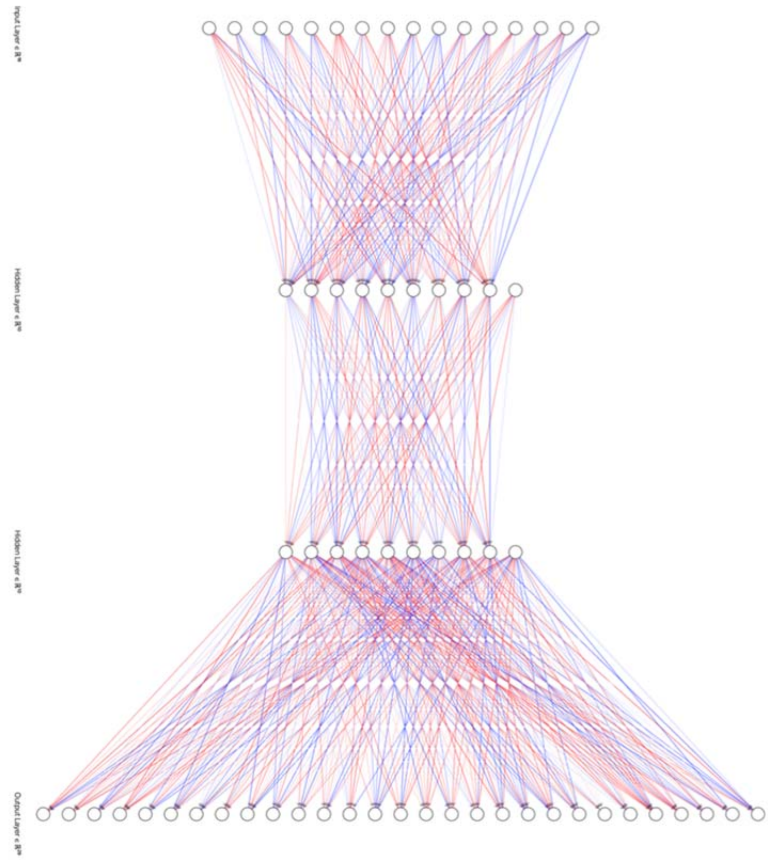


Figure 4. 2. Architectural Visualization of Artifical Neural Network

After Artificial Neural Network was trained, system healthy verified by test data. Test results showed that there is %63.2 accuracy rate on testing.

By this network, main intention is that predicting words starting from 2 letter word up to 5 letter word.

For 2 letter words, “AH, “BU”, SU” has chosen.

For “AH” predictions coming letters are shown below.

AH
A
AA
AAA
AAAG

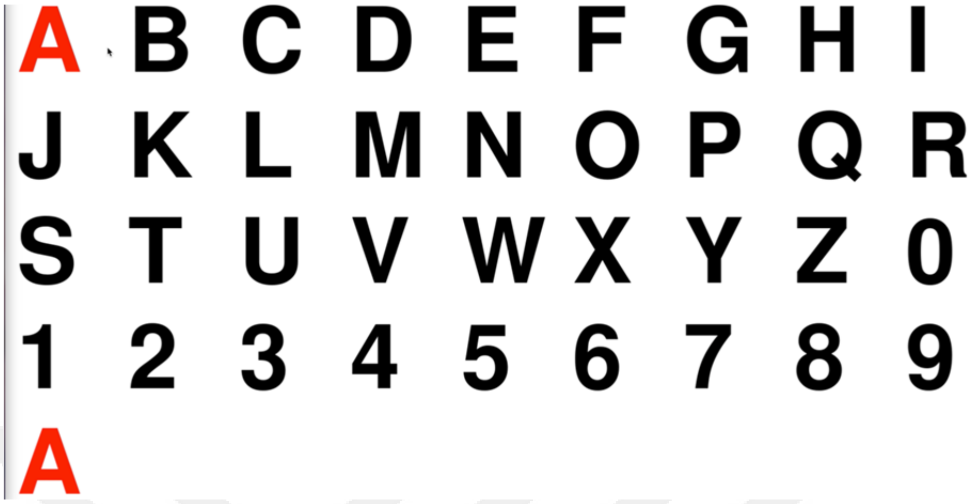


Figure 4.3. Letter Capturing Order Has Been Shown.

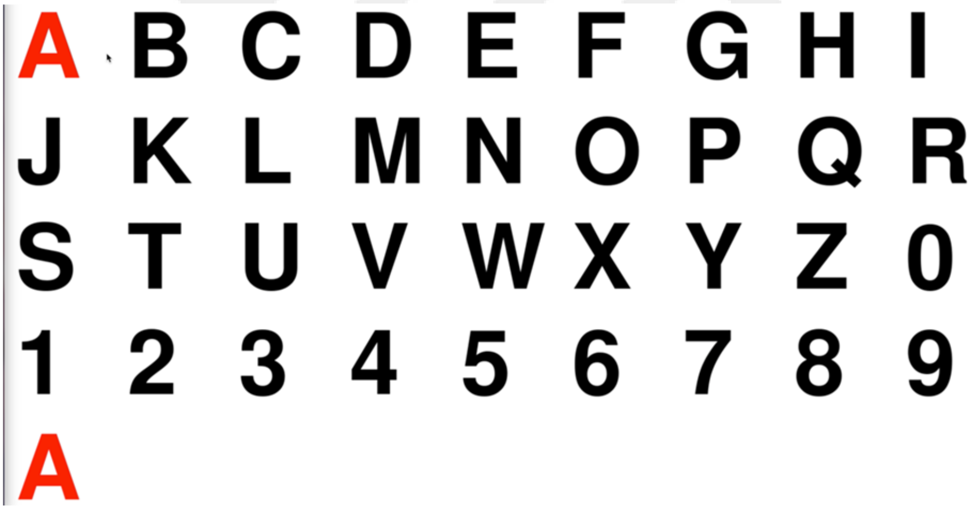


Figure 4.4. Shows That Letter A Being Captured Second Time During Prediction of A

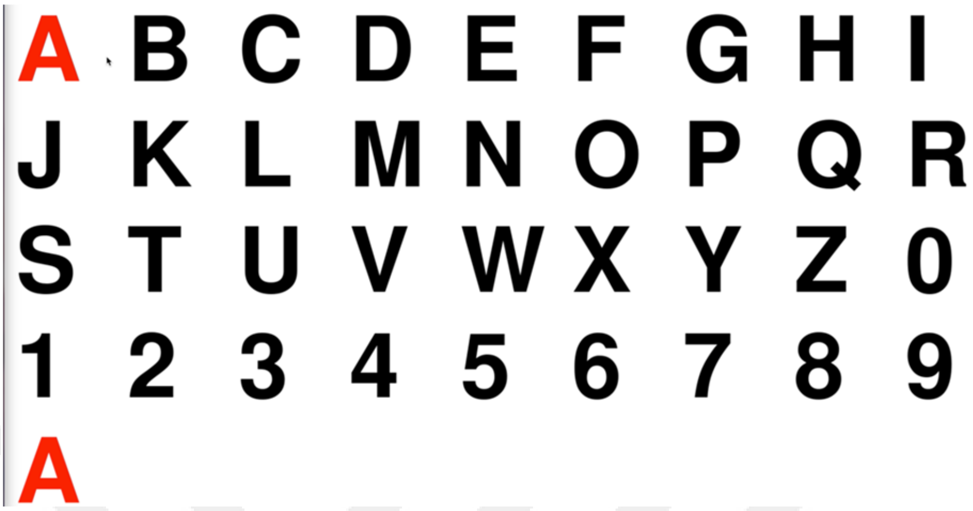


Figure 4.5. Shows That Letter A Being Captured Third Time During Prediction of A

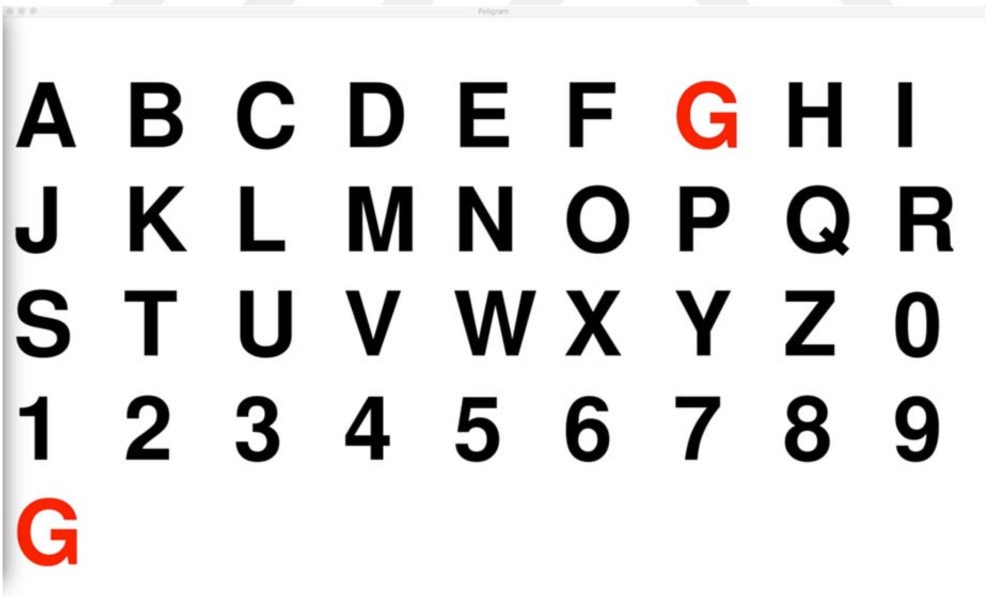


Figure 4.6. Shows That Letter G Being Captured First Time During Prediction of G

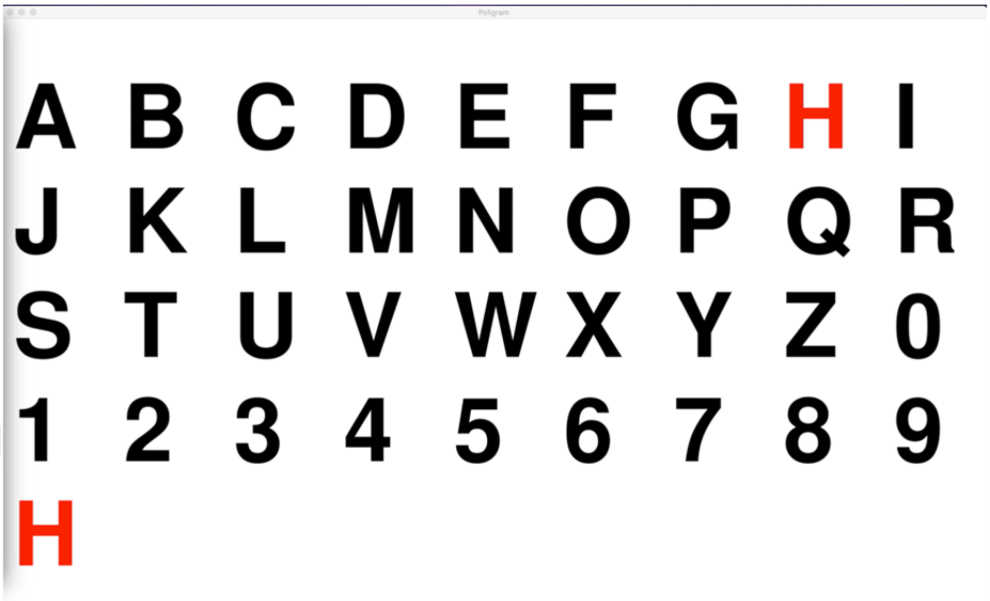


Figure 4.7. Shows That Letter H Being Captured Second Time During Prediction of H

While capturing EEG signal activity changes, the signal changes are observed below in data. From, first, second, nineth and eleventh channels, there is absulate signals changes are observed.

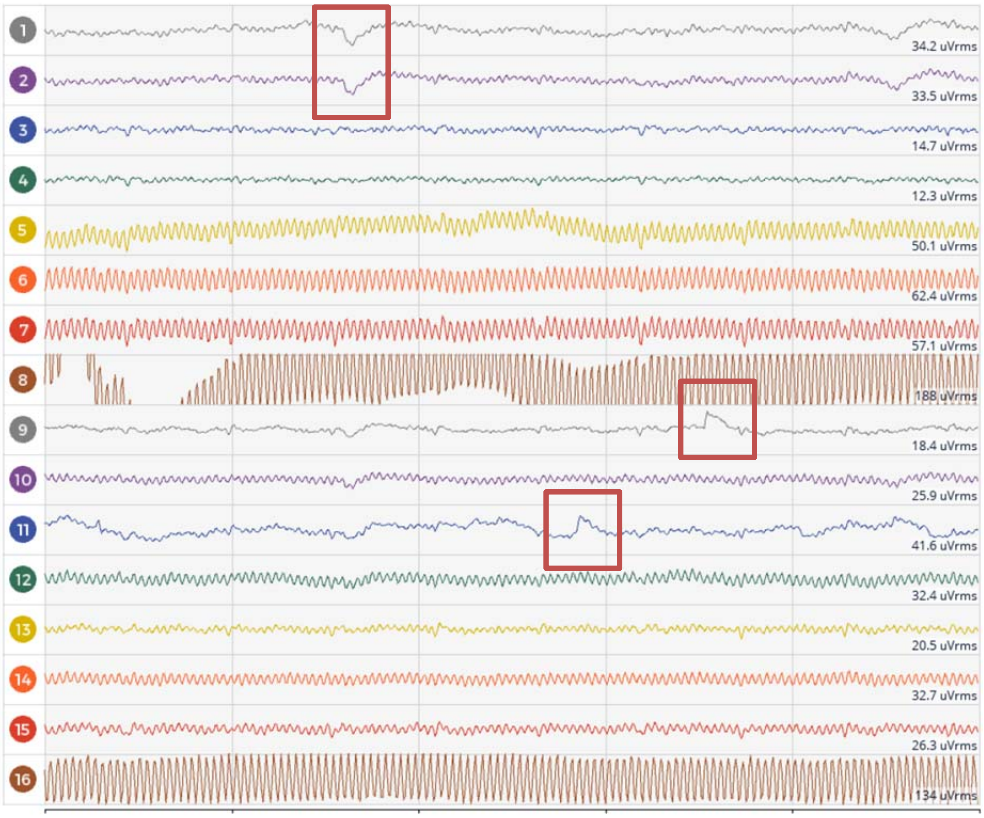


Figure 4.8. Shows Signal Activity Changes During Capturement of Letters

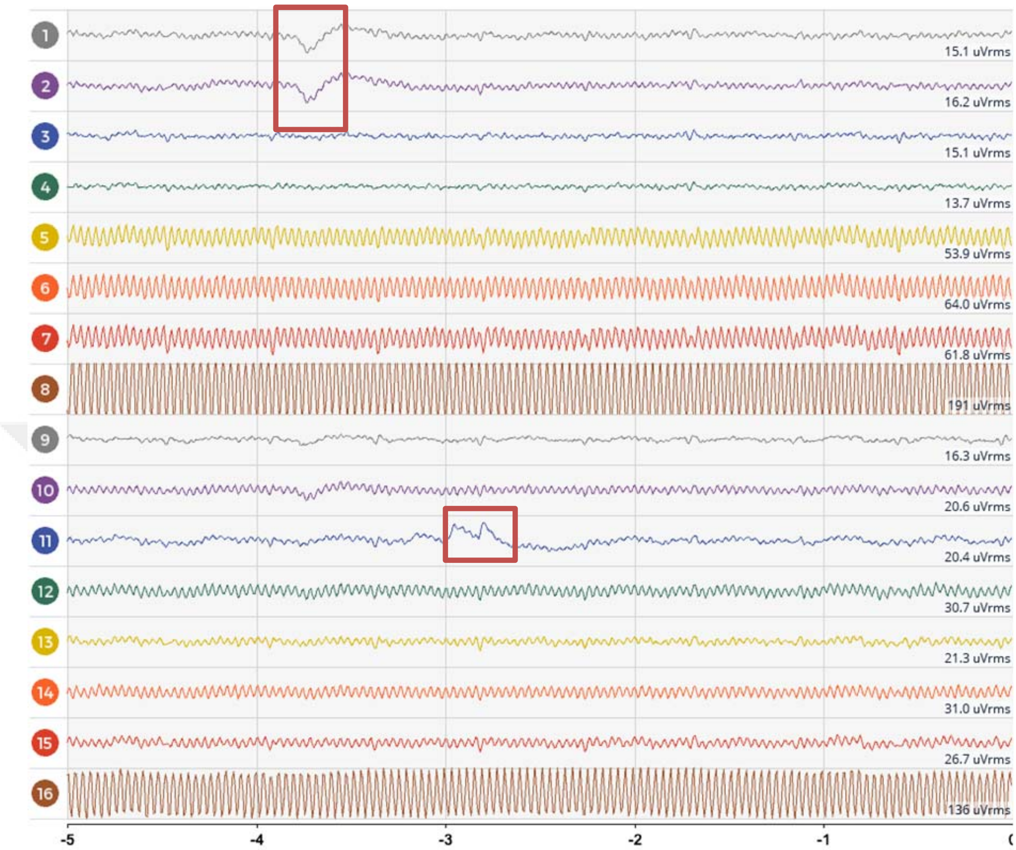


Figure 4.9. Above, Significant EEG Signal Changes Observed Below During ‘A’ and H Letter are Being Captured.

Another word was being captured “**SU**” and **“BU”**. Following results came up below.

SU	**BU**
S	L
SS	LB
SSS	LBL
SSSS	LBLU
SSSSSU	LBLUB

As 3 letter words, “KEK”, “EBE”, “EFE” “ATA” were used on this experiement. For the word “KEK” following order are captured below.

KEK
K KK KKK KKKEKRK

During that process, in the below screenshow, it can be observed following captured letters and signal changes that were being captured and determined.

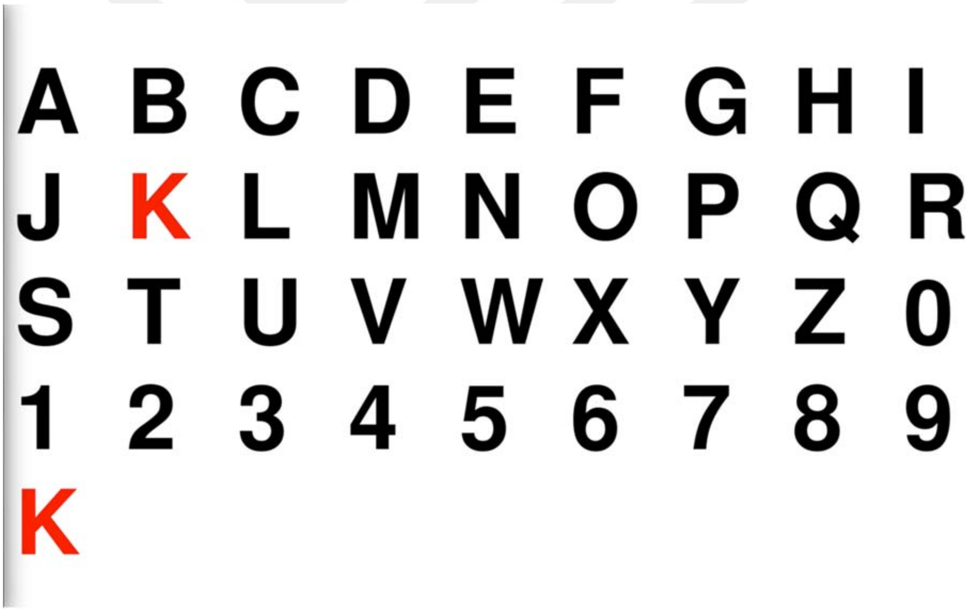


Figure 4.10. Shows That Letter K Being Captured First Time During Prediction of K

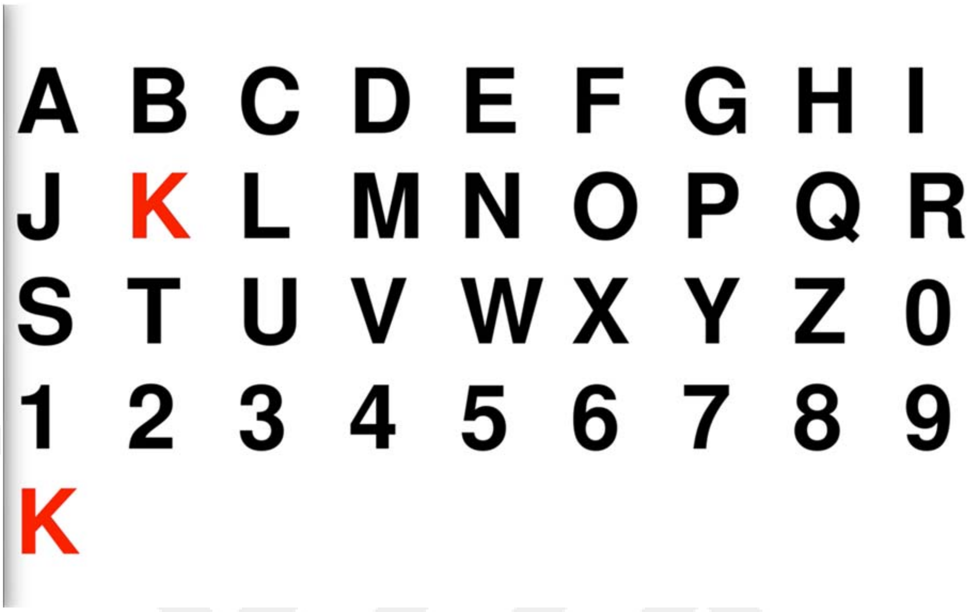


Figure 4.11. Shows That Letter K Being Captured Second Time During Prediction of K

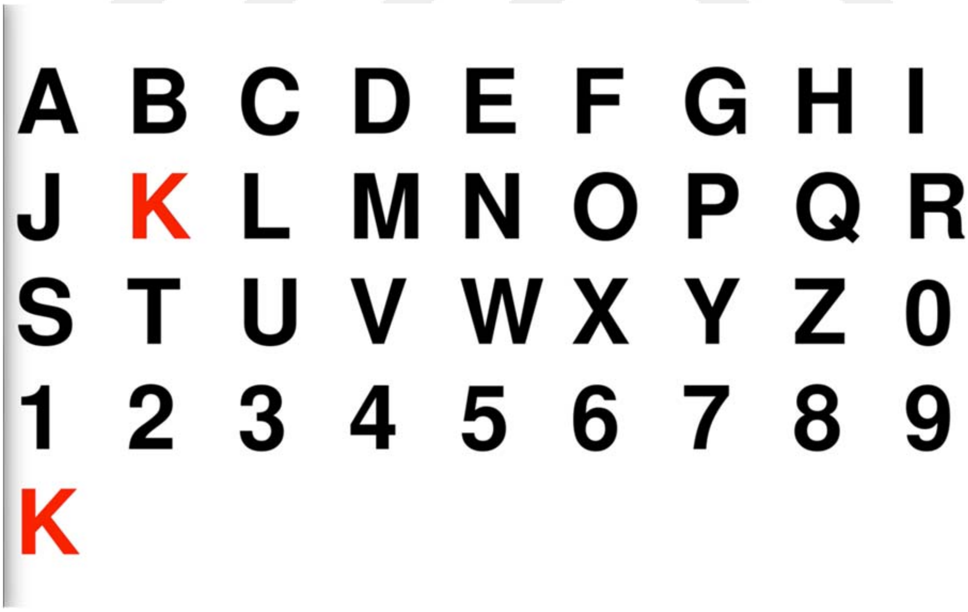


Figure 4.12. Shows That Letter K Being Captured Third Time During Prediction of K

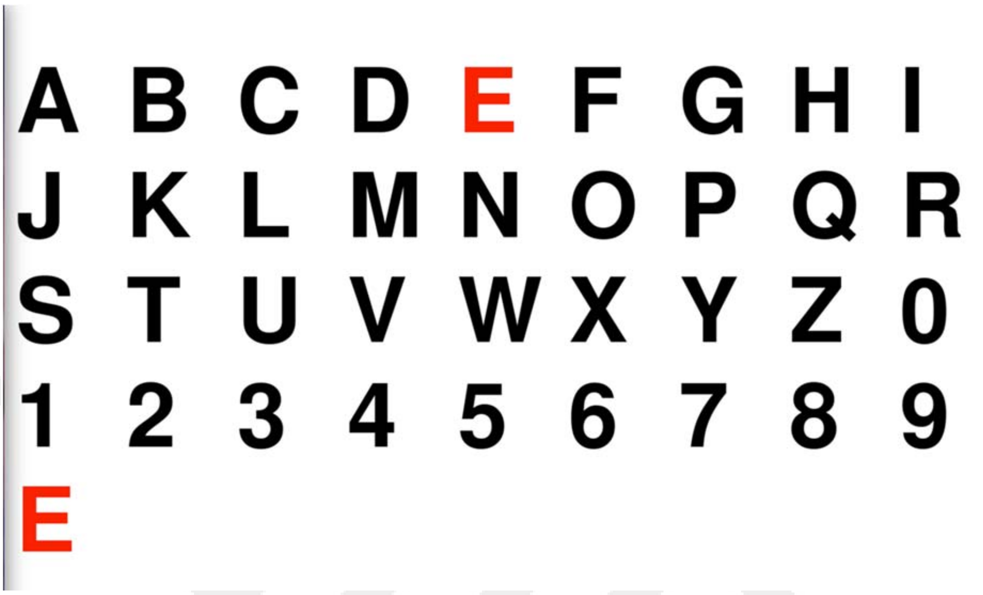


Figure 4.13. Shows That Letter E Being Captured During Prediction of E

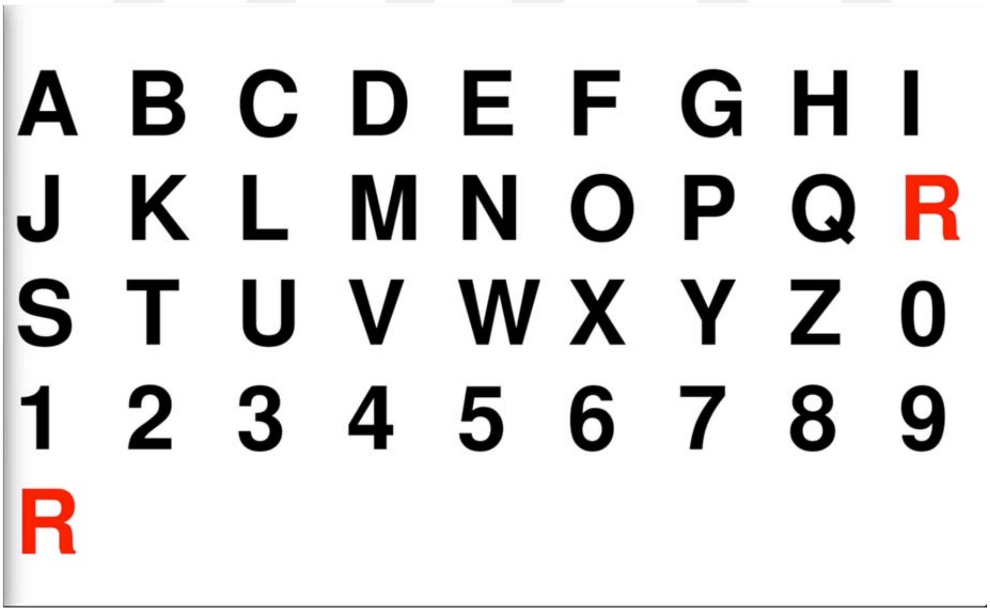


Figure 4.14. Shows That Letter R Being Captured During Prediction of R

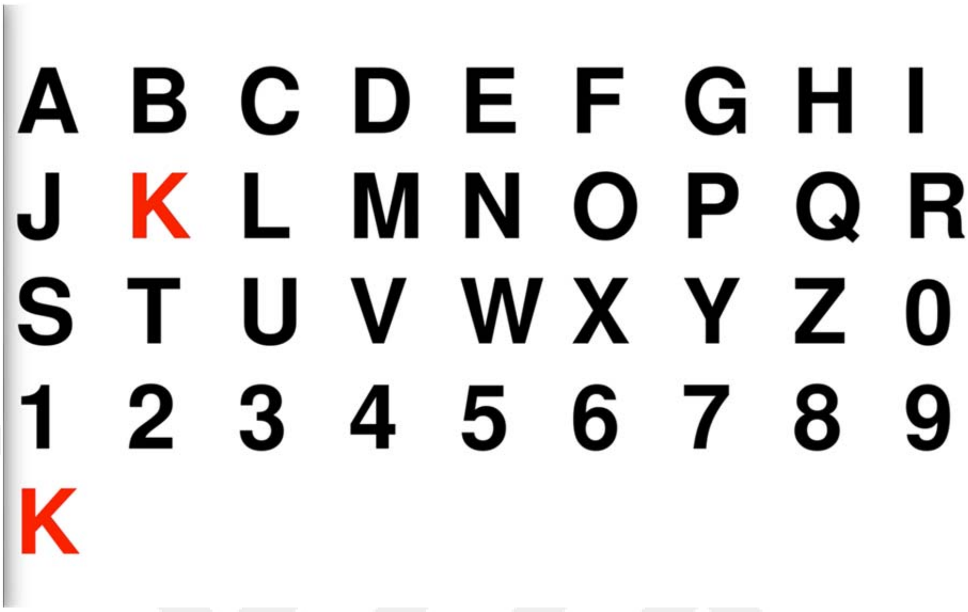


Figure 4.15. Shows That Letter K Being Captured Third Time During Prediction of K

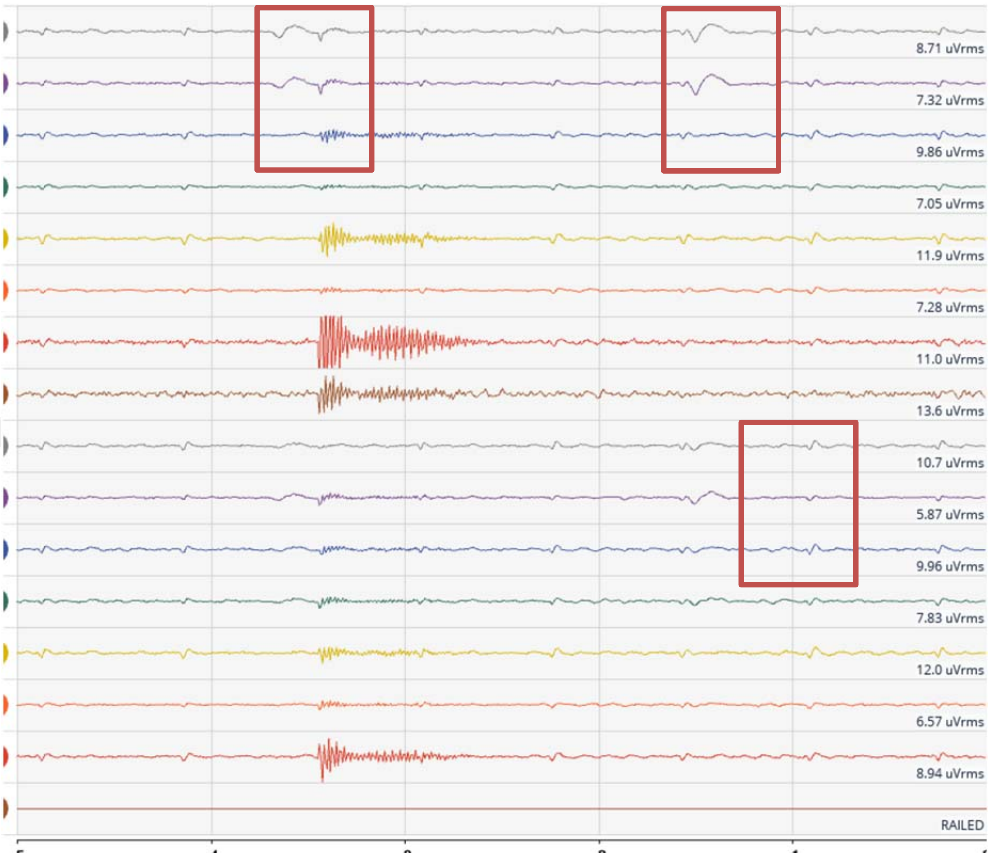


Figure 4.16. Shows That Letter R Being Captured Third Time During Prediction of R

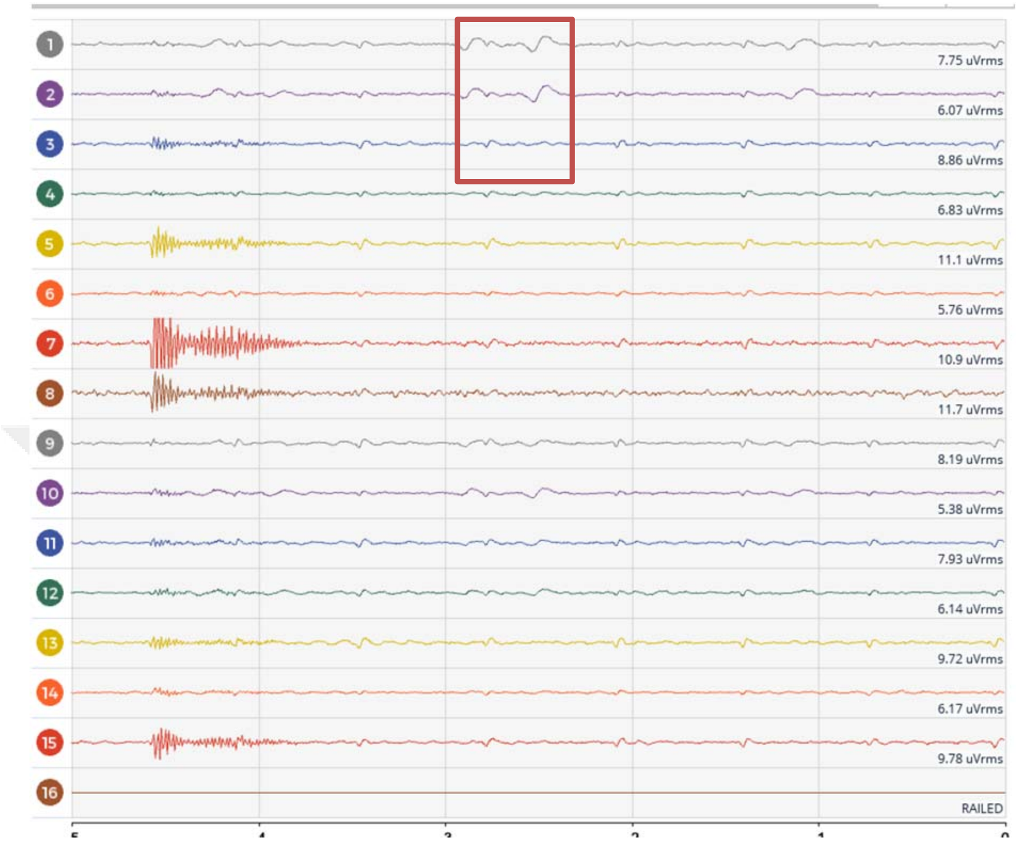


Figure 4.17. EEG Activity

For the upcoming words of "EBE", "EFE", "ATA" following order of letters were stated.

EBE	EFE	ATA
E EB EBE EBEE EBEEB EBEEBB EBEEBBT EBEEBBTE EBEEBBTEE	E EE EEV EEVE EEVEV EEVEVV EEVEVVV EEVEVVVF EEVEVVVFF EEVEEVVVFFFE	A AT ATA

As 4 letter words, "SEFA", "KEFE", "TEFE", "KAFE" choosed.

For “SEFA” recognized letters and EEG signal changes were shown below.

SEFA
A AS ASE ASEFK ASEFKS ASEFKSF ASEFKSFA

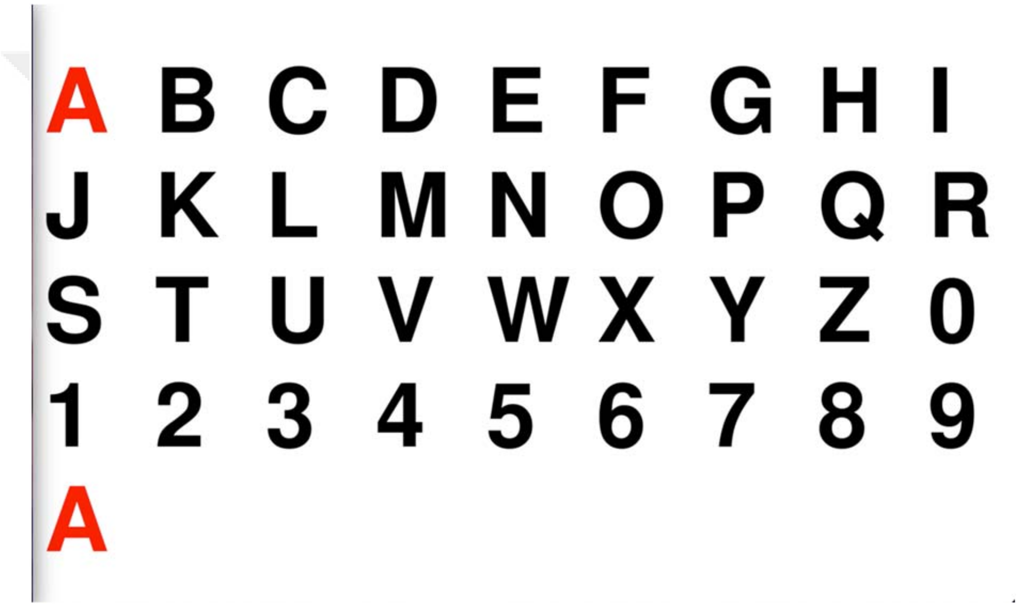


Figure 4.18, A Has Captured as First Letter.

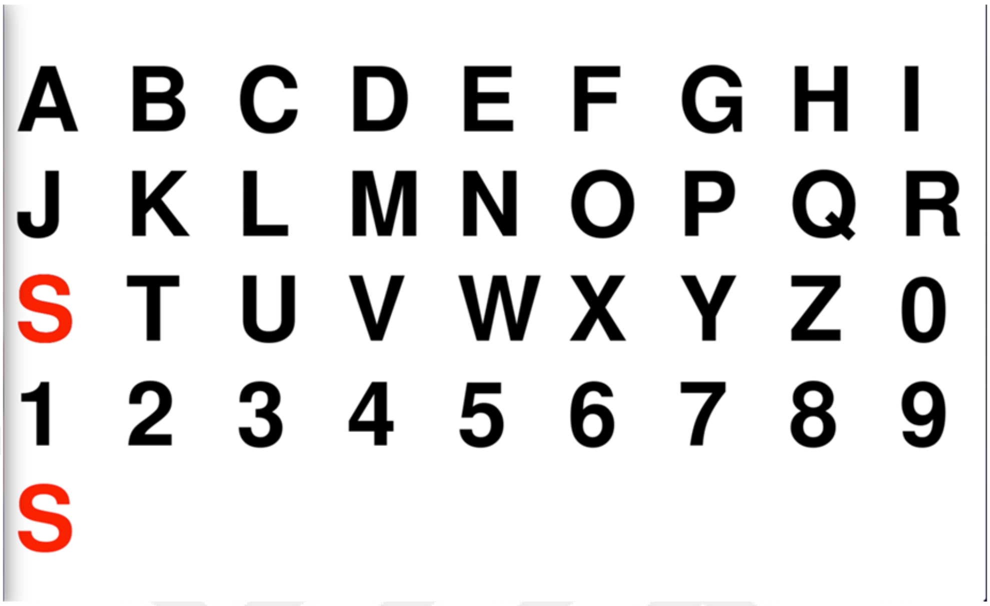


Figure 4.19. As Following Letter S Has Been Captured. It Has Shown below

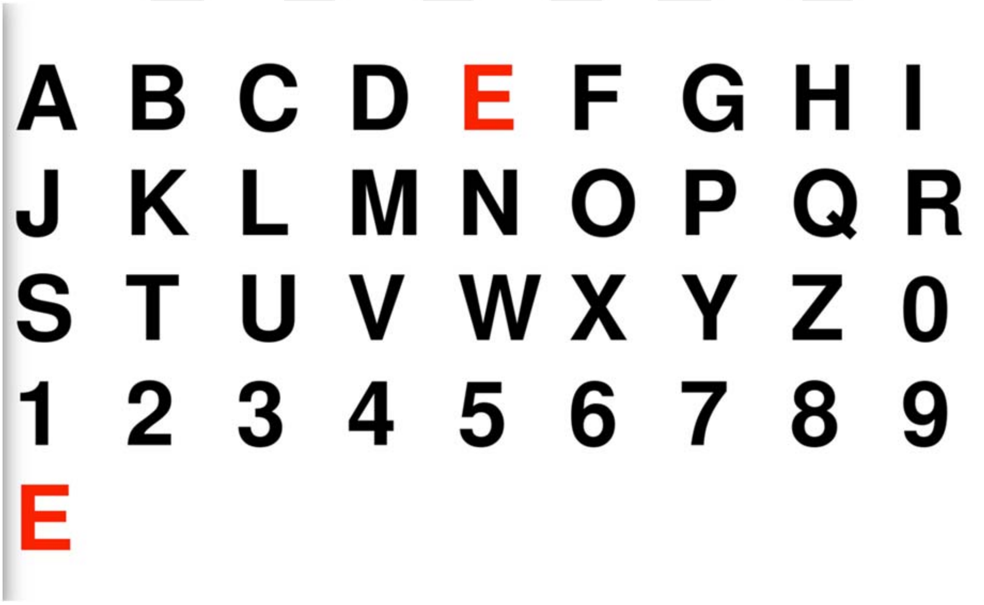


Figure 4.20. E Has Captured.

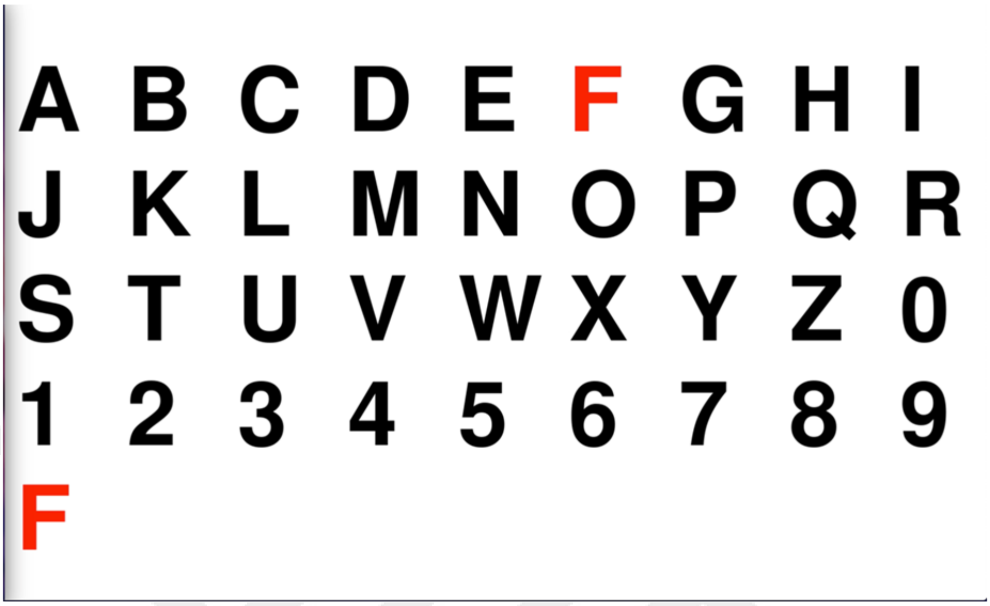


Figure 4.21. F Is Another Word Has Been Captured. it Has Shown In

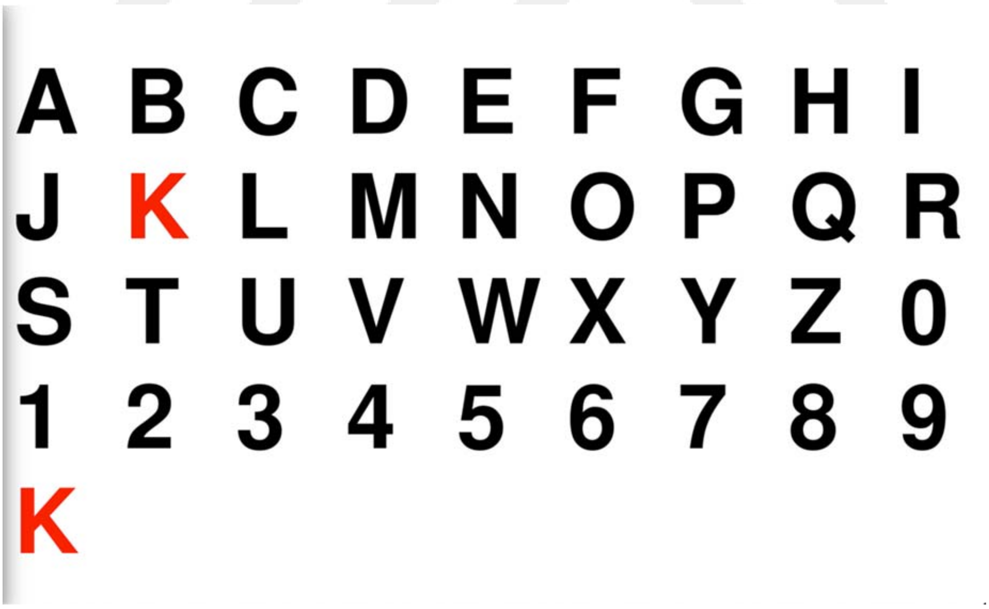


Figure 4.22. K Has Been Determined After F. Shows That State.

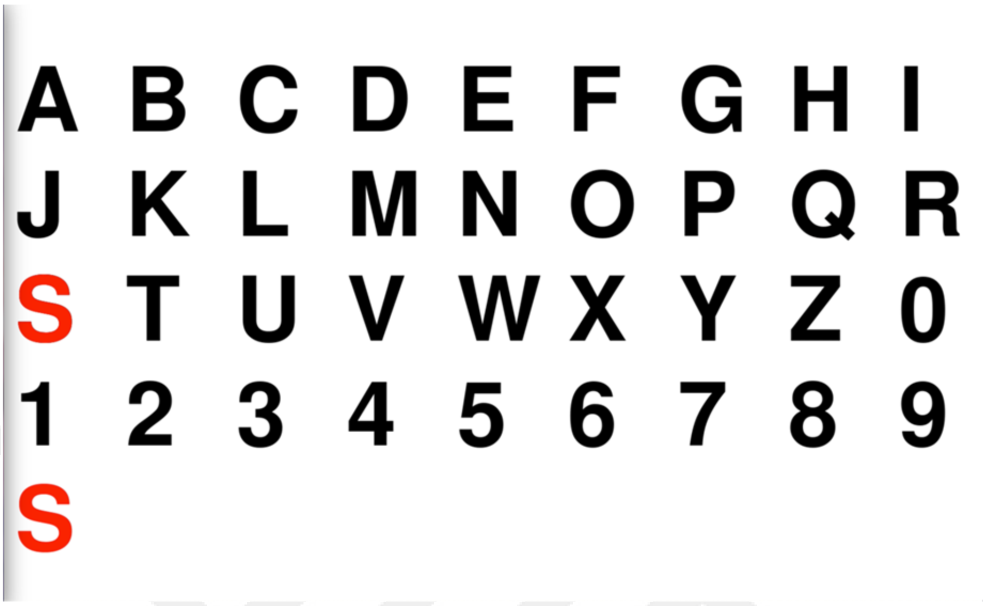


Figure 4.23. S Has Captured After K Letter.

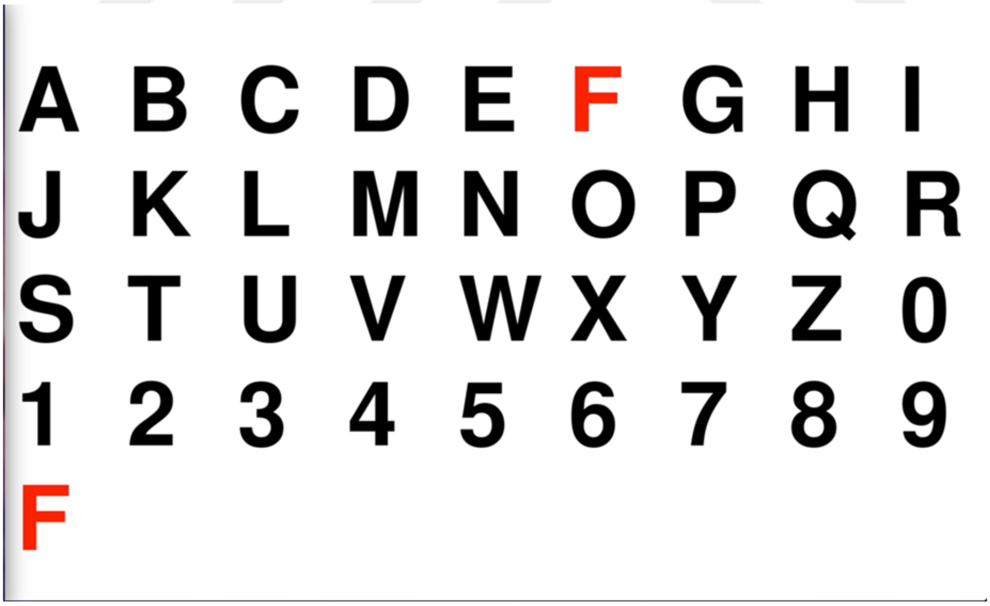


Figure 4.24. F Letter Has Been Determined by Recognizing Application Above

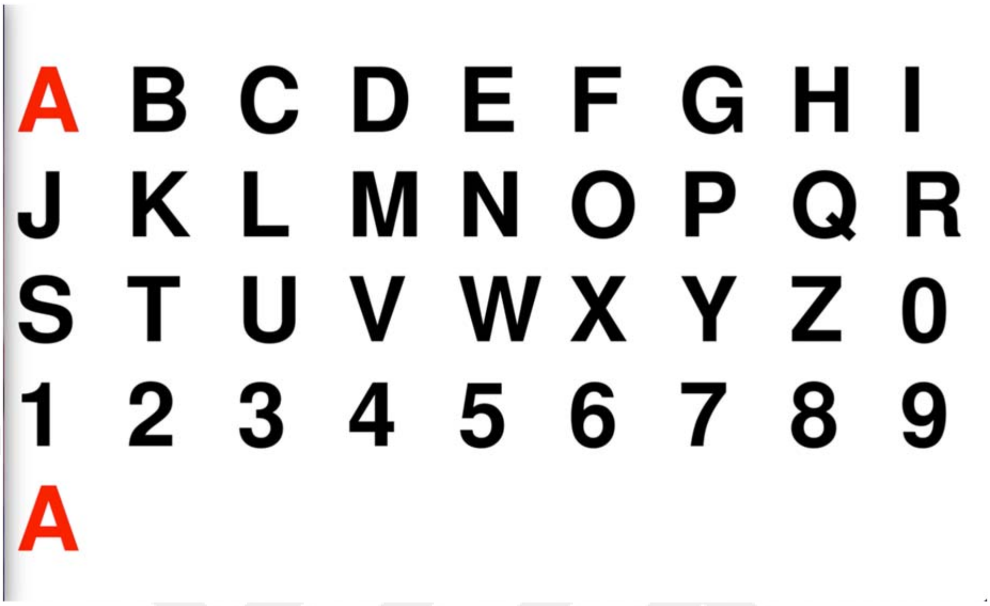


Figure 4.25. A is The Last Final Word to Complete All Letters.

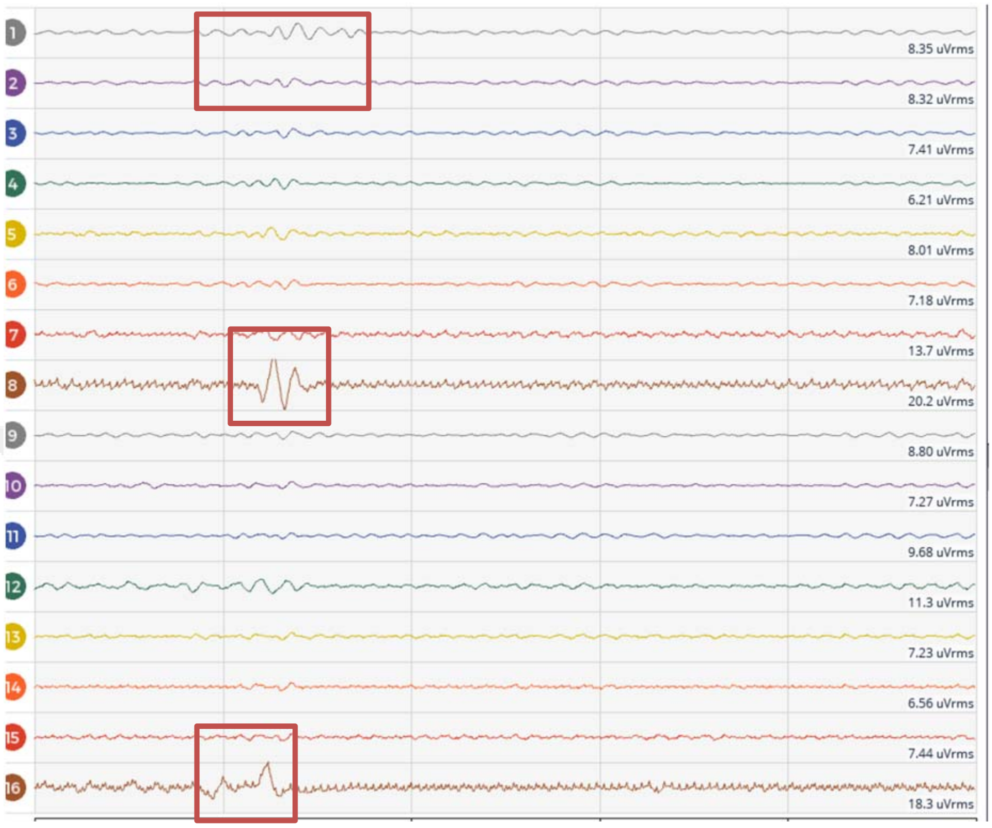


Figure 4.26. Some Significant Change Of EEG Activites Are Shown in Figure Above.

For “KEFE”, “TEFE”, “KAFE” following determination of letters are below.

KEFE	TEFE	KAFE
	T	K
	TT	KK
	TTR	KKK
	TTRE	KKKK
	TTREE	KKKKM
	TTREEM	KKKKMA
	TTREEMF	KKKKMAA
	TTREEMFL	KKKKMAAA
	TTREEMFLE	KKKKMAAAA
		KKKKMAAAAF
		KKKKMAAAAFP
		KKKKMAAAAFPP
		KKKKMAAAAFPPE

As 5 letter words, "MUTLU". For "MUTLU" you can see the captured letters below.

MUTLU
J
JM
JML
JMLU
JMLUU
JMLUUT
JMLUUTJ
JMLUUTJL
JMLUUTJLL
JMLUUTJLLL
JMLUUTJLLLT
JMLUUTJLLTU

In the following, EEG Signal differentiation samples and captured letters screenshots are below.

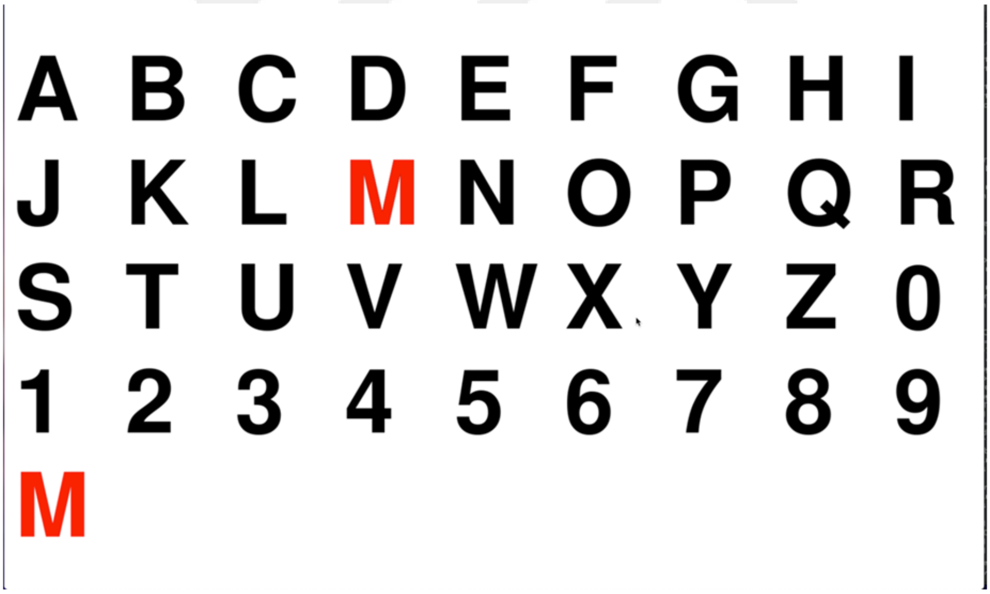


Figure 4.27. As First Letter M Has Captured

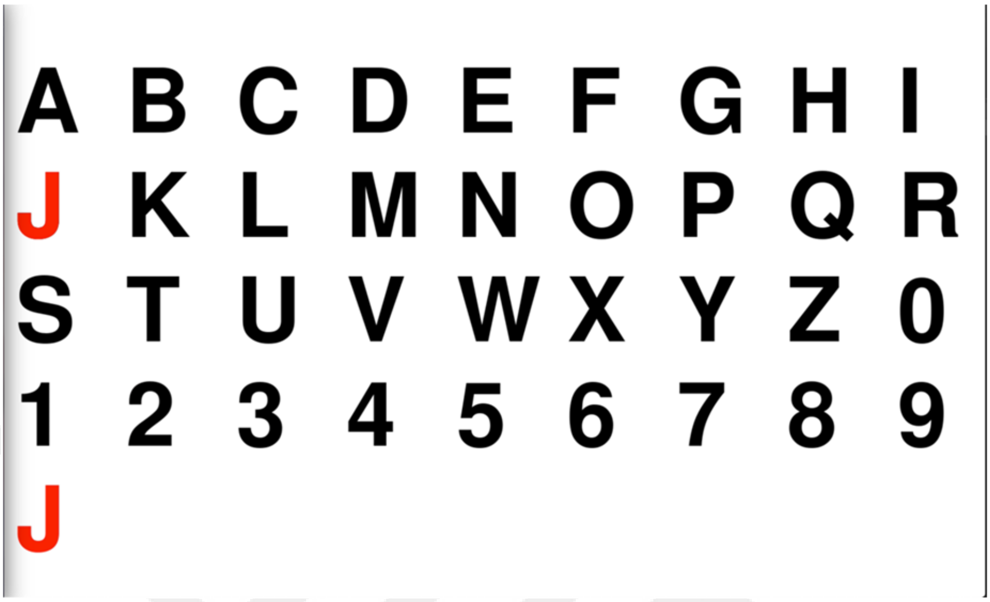


Figure 4.28. After “M”, “J” Has Captured Through Developed Application

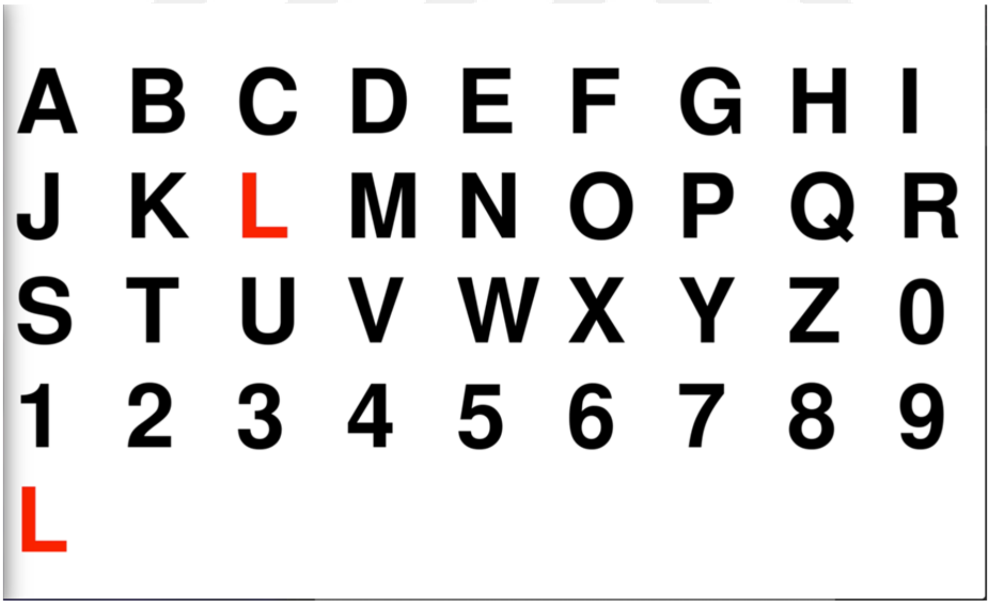


Figure 4.29. As Third Letter, L Has Been Spelled

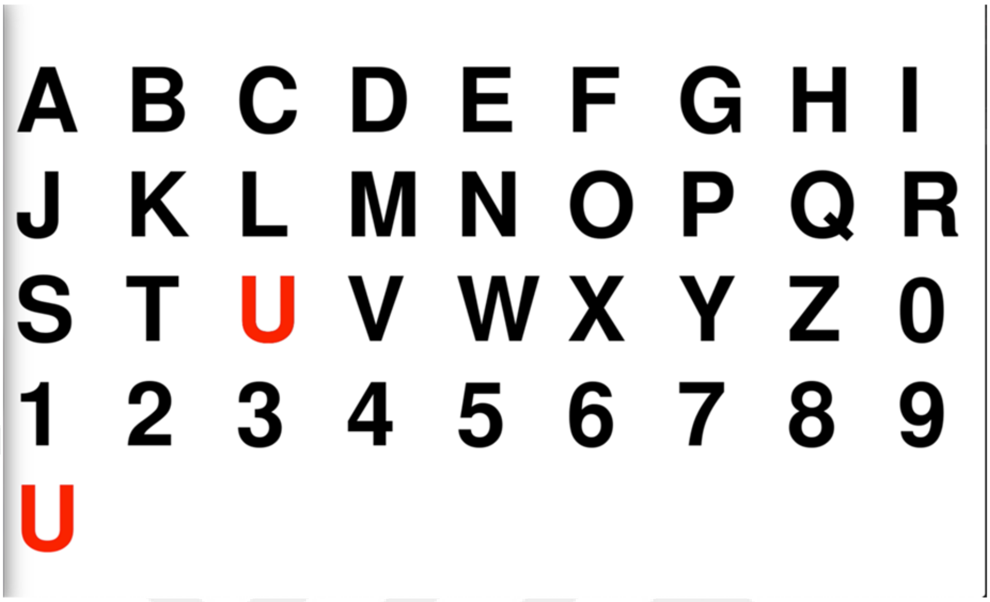


Figure 4.30. It States That U Has Captured As Following Letter.

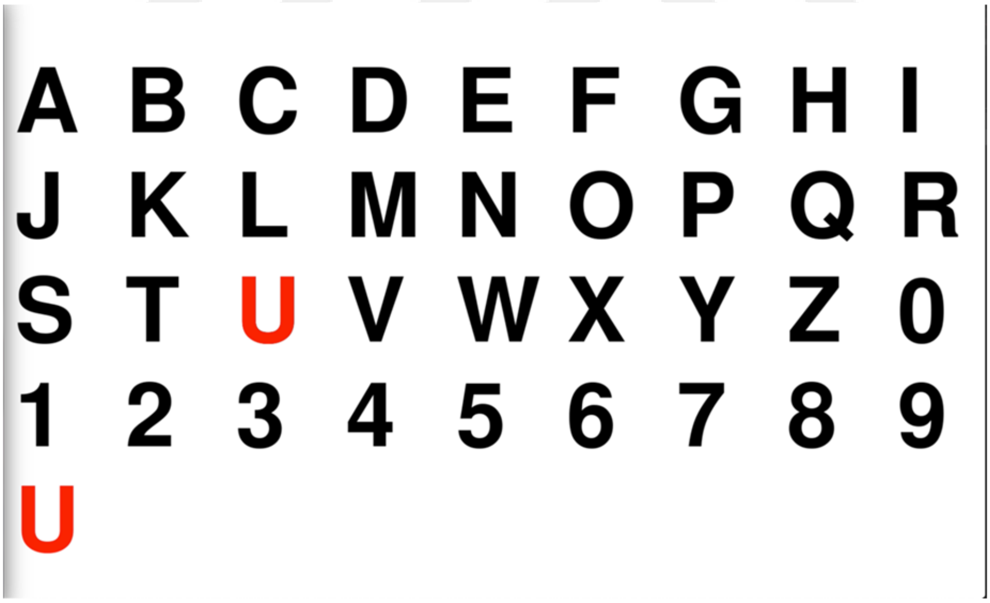


Figure 4.31. Another U Has Captured

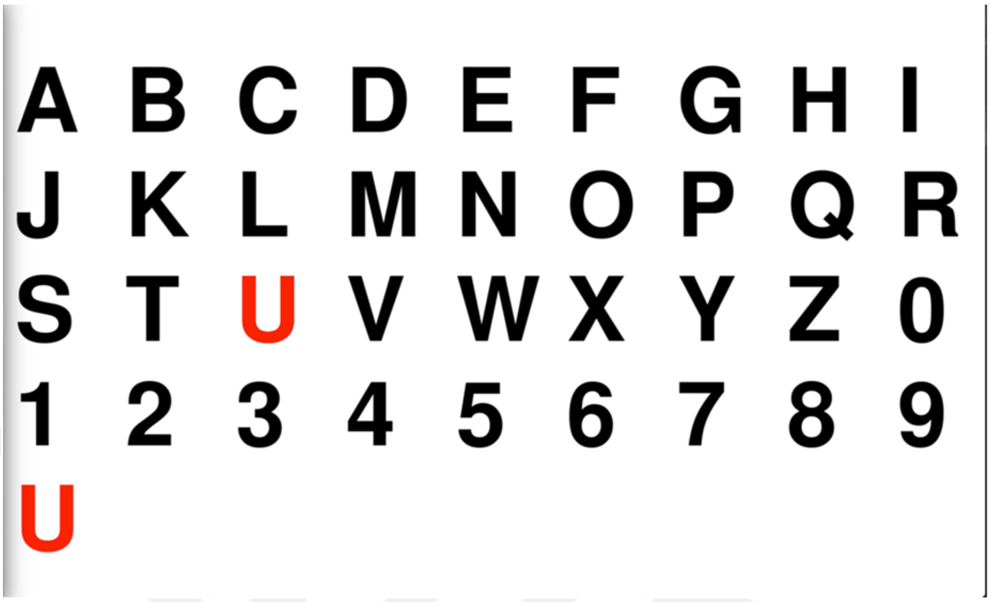


Figure 4.32. Additional U Has Been Captured

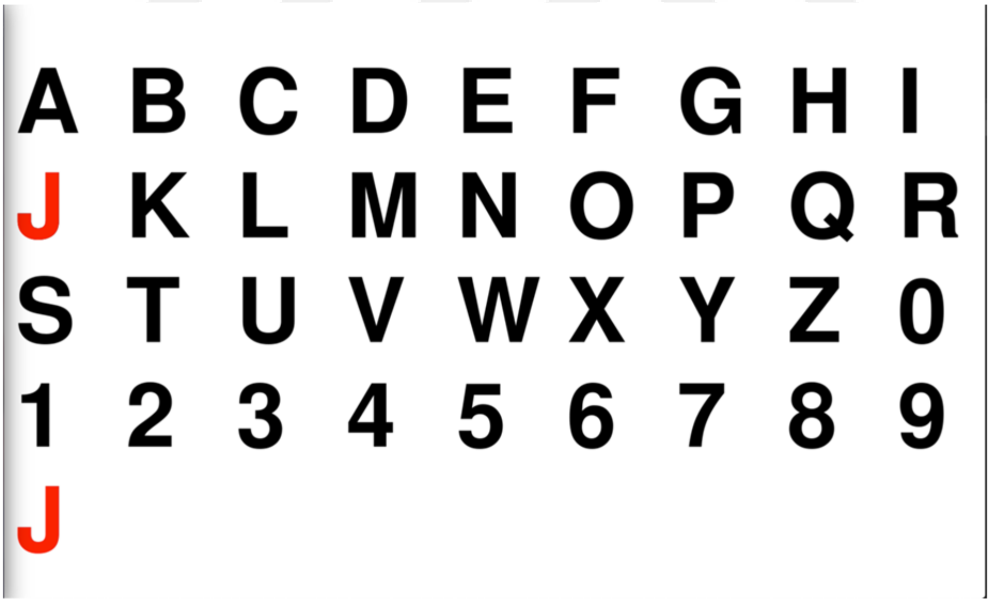


Figure 4.33. J Has Been Determined Additionaly After 3 “U” Letter.

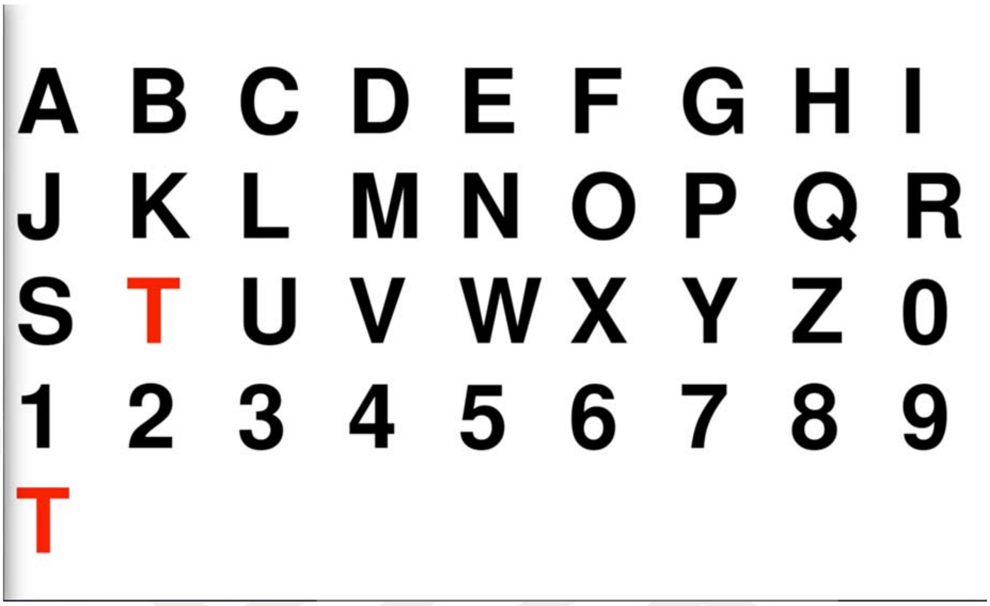


Figure 4.34. T Has Spelled After “J”.

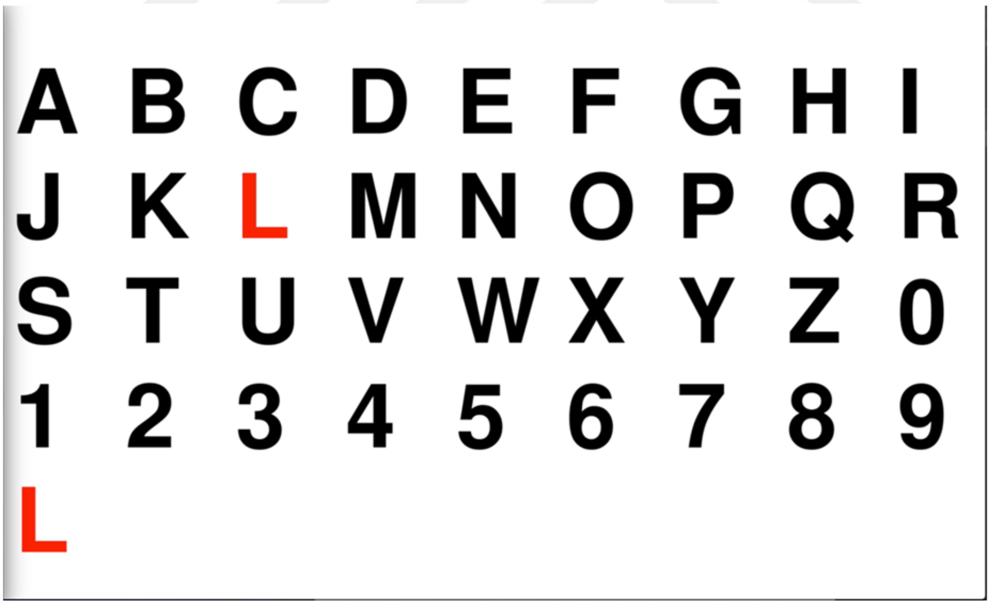


Figure 4.35. L Has Been Captured.

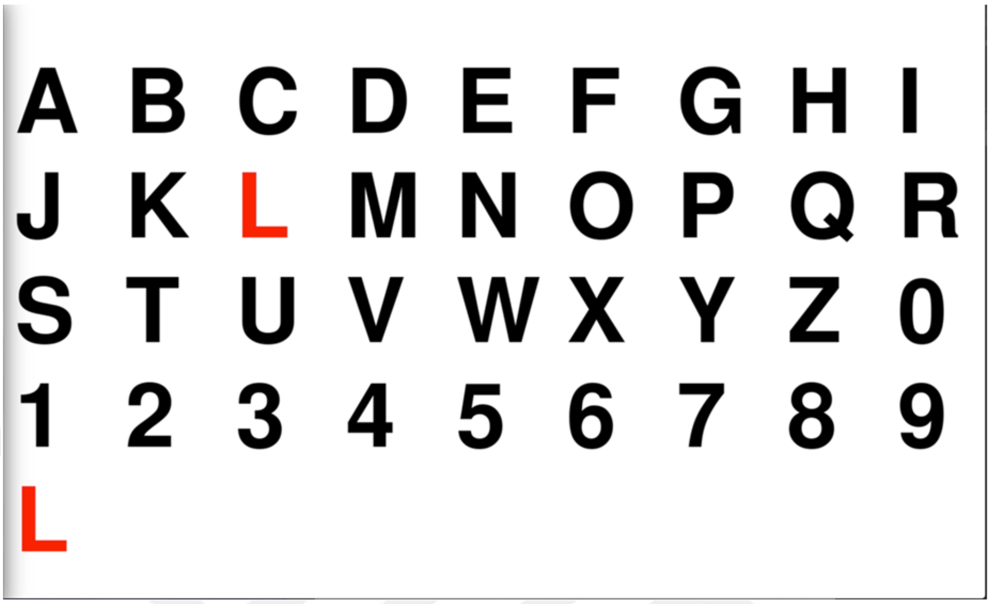


Figure 4.36. Second “L” Has Been Captured.

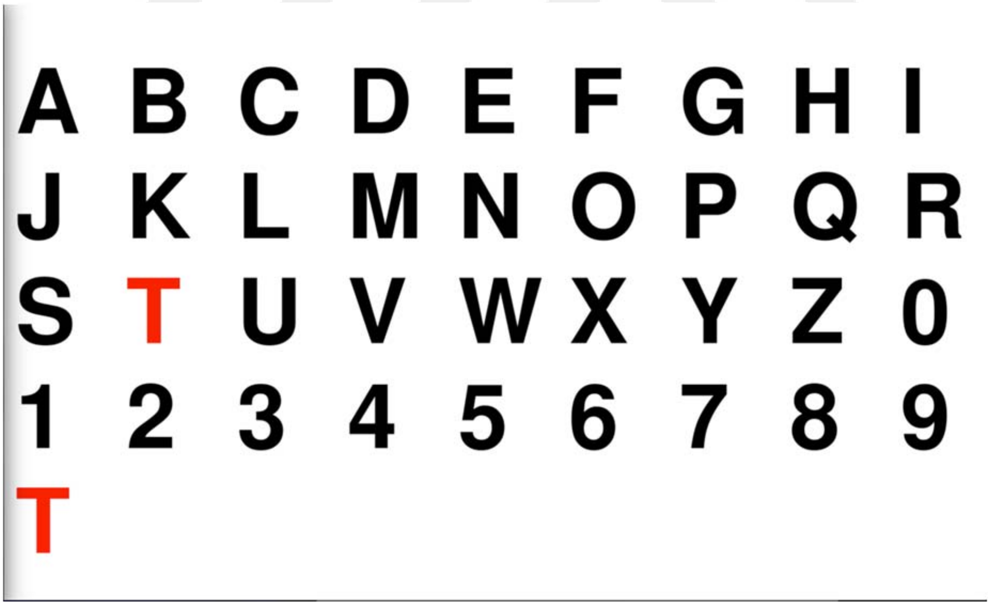


Figure 4.37. T Was Appeared on Spelling Screen

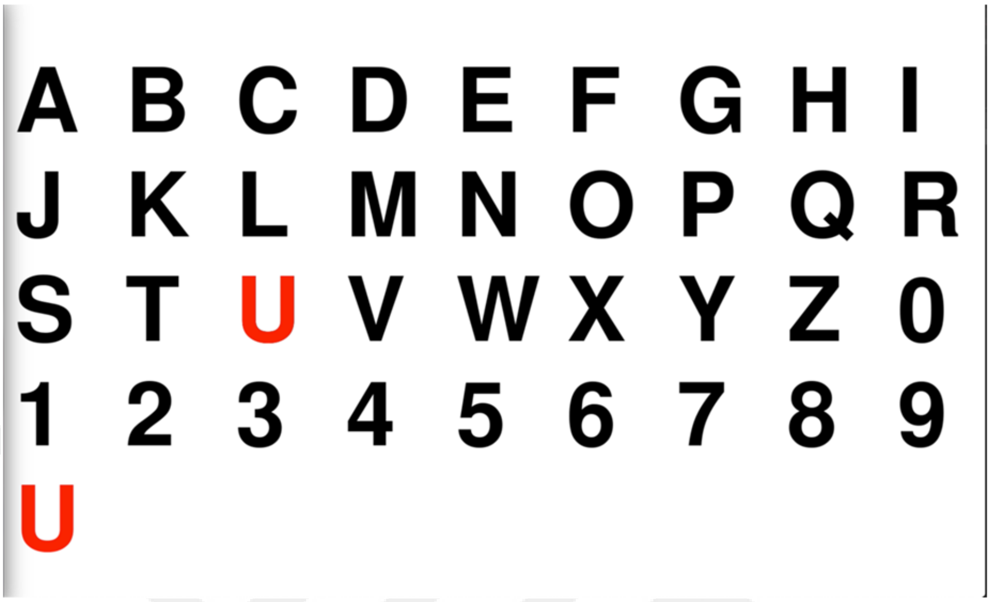


Figure 4.38. U Was Appeared on Spelling Screen

5. RESULTS AND DISCUSSION

The subject-matter work is an integral constituent of the front-end design of a portable, inexpensive, and user-friendly neonatal EEG acquisition and interpretation system. This thesis provides a precise and cost-effective platform with the intention of assessing the accuracy and excellence of EEG recording hardware. The elimination of human subjects in the process also eliminates the issues pertaining to health/safety and ethics. The work also paved the way for iterative evaluation of novel EEG systems with ease and pace. The losses stem from the very nature of the digital to analog conversion and down-scaling were managed to be made minimal. The EEG acquisition system in this work attained high accuracy in comparison with the original EEG signal in the databese. Considering the usage of dry electrodes besides using wet electrodes resulted in the proof that dry EEG electrodes have higher skin-electrode impedance.

6. CONCLUSION AND FUTURE WORKS

This thesis is an investigation into the human brain and the low-cost EEG headset "OpenBCI". The feasiblity of using the cost effective Eeg headset device for educational purposes in the Cukurova University is also studied. Reasons such as lack of experience in using the device prevented this purpose to be accomplished. A rigorous study on the human brain and EEG was carried out to explain the work of functioning of EEG signals with low-cost BCI devices. After that, an effort was made to learn profoundly the low EEG OpenBCI and the fields that the device can be utilized with gaming purposes.

In the course of the project, various EEG measurements were conducted on the brain through the OpenBCI device. The measurements were made at distinct time periods and in different states of subjects mind. Therefore variable EEG measurements were achieved. It is understood that EEG data can be analyzed to predict or find out a persons state of mind.

EEG of the brain, FFT, power spectrum of the brain waves could be observed thanks to the device and the related computer software. It is also observed the level of activity of different segments of the brain. It is concluded that brain waves can be manipulated by some methods by altering the condition of the subject human. These manipulations are performed by authorized personnel or doctors. It is possible to boost the relatively less active segment of the brain and alter the theoverall brain function.

Even 100 % achievement may not be attained scientists and scholars struggle to fulfill their objectives by learning from mistakes and courageously embrace obstacles they face. The device and the software are not commercially offered to be used for research and educational purposes. Cukurova University can provide considerable space for the teaching of education-based software to medical engineering students in the event that it is developed and the related research is carried out.

REFERENCES

Allison, B. Z. and Pineda, J. A. (2003) "ERPs evoked by different matrix sizes: Implications for a brain computer interface (BCI) system," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 11(2), pp. 110–113. doi: 10.1109/TNSRE.2003.814448.

Chiesi, M. *et al.* (2019) "Creamino: A Cost-Effective, Open-Source EEG-Based BCI System," *IEEE Transactions on Biomedical Engineering*. IEEE, 66(4), pp. 900–909. doi: 10.1109/TBME.2018.2863198.

Cuntai Guan *et al.* (2006) "A high-performance brain–computer interface," *Nature*. IEEE, 442(7099), pp. 195–198. doi: 10.1038/nature04968.

Cuntai Guan, Thulasidas, M. and Jiankang Wu (2005) "High performance p300 speller for brain-computer interface," pp. 293–296. doi: 10.1109/biocas.2004.1454155.

Fazel-Rezai, R. *et al.* (2012) "P300 brain computer interface: Current challenges and emerging trends," *Frontiers in Neuroengineering*, 5(JUNE), pp. 1–30. doi: 10.3389/fneng.2012.00014.

Guan, C., Thulasidas, M. and Wu, J. (2004) "High performance P300 speller for brain-computer interface," in *2004 IEEE International Workshop on Biomedical Circuits and Systems*. doi: 10.1109/biocas.2004.1454155.

Nijboer, F. *et al.* (2008) "A P300-based brain-computer interface for people with amyotrophic lateral sclerosis.," *Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology*. NIH Public Access, 119(8), pp. 1909–1916. doi: 10.1016/j.clinph.2008.03.034.

Salvaris, M. and Sepulveda, F. (2009) "Perceptual errors in the farwell and donchin matrix speller," *2009 4th International IEEE/EMBS Conference on Neural Engineering, NER '09*. IEEE, pp. 275–278. doi: 10.1109/NER.2009.5109286.

Sun, F., Hu, D. and Liu, H. (2014) *Foundations and Practical Applications of Cognitive Systems and Information Processing: Proceedings of the First International Conference on Cognitive Systems and Information Processing, Beijing, China, Dec 2012 (CSIP2012)*. doi: 10.1007/978-3-642-37835-5.

Tada, M. *et al.* (2019) "Mismatch negativity (MMN) as a tool for translational investigations into early psychosis: A review," *International Journal of Psychophysiology*. Elsevier, 145(March), pp. 5–14. doi: 10.1016/j.ijpsycho.2019.02.009.

Zhang, Z. and Deng, Z. (2014) "An automatic SSVEP component selection measure for high-performance brain-computer interface," *Advances in Intelligent Systems and Computing*, 215, pp. 93–108. doi: 10.1007/978-3-642-37835-5_9.

CURRICULUM VITAE

Ibrahim Sefa ÖZYEŞİL was born in Ankara, Turkey in 1989. He received his B.S. degree in Computer Engineering Department from Çukurova University in 2014. After completion his B.S. education, he started MSc education in Biomedical Engineering Department in Çukurova University in 2012. He has been working as Software Engineer in IT Industry since 2013. His research areas are Machine Learning, Artificial Neural Network, Brain Computer Interface.