Real-Time Emotion Detection using EEG Machine

Project report submitted in partial fulfillment of the requirement for the degree of Bachelor of Technology

In

Information Technology

By

Shubham Singla (131406)

Shubhi Garg (131420)

Under the supervision of

Dr. Pradeep Kumar Singh

to

Department of Computer Science & Engineering and Information Technology

Jaypee University of Information Technology Waknaghat, Solan-173234, Himachal Pradesh

CERTIFICATE

Candidate's Declaration

This is to certify that the work which is being presented in the report entitled **"Real-Time Emotion Detection using EEG Machine"** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering/Information Technology** submitted in the department of Computer Science & Engineering and Information Technology**,** Jaypee University of Information Technology Waknaghat is an authentic record of our own work carried out over a period from August 2016 to May 2017 under the supervision of **Dr. Pradeep Kumar Singh** (Assistant Professor, Computer Science & Engineering Department).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

Shubham Singla (131406)

Shubhi Garg (131420)

This is to certify that the above statement made by the candidates is true to the best of my knowledge.

Dr. Pradeep Kumar Singh

Assistant Professor (Senior Grade)

Computer Science & Engineering Department

Dated: 02/05/2017

ACKNOWLEDGEMENT

It is immense pleasure to present this report on the project named "**Real-Time Emotion Detection using EEG Machine**" embraced by us as a major aspect of our B. Tech (IT) educational curriculum.

We are grateful to our University (Jaypee University of Information Technology) for offering us such a wonderful opportunity and we have taken endeavors in this project and it is a delight that we find our self-penning down these lines to express our earnest thanks to the people those who helped us in successfully completing our project. We profoundly express our sincere thanks to our Project Coordinator Dr. Yashwant Singh for urging and enabling us to present this project at our specialization premises for partial fulfillment of necessities prompting the honor of B-Tech degree.

Most importantly, we might want to offer our thanks towards our project guide - Dr. Pradeep Kumar Singh for placing complete confidence and trust in our ability to do this project and for giving us his time, motivation, help, guidance, and constant interest. Without the earnest and honest guidance of our respected project guide we would have not been to achieve the present stage.

Date: 22/04/2017 Shubham Singla

Shubhi Garg

Contents

ABBREVIATIONS

Sr No.	Abbreviated form	Full form
1	EEG	Electroencephalogram
2	SVM	Support Vector Machine
3	IOT	Internet of Things
4	BCI	Brain Computer Interface
5	ADHD	Attention Deficit Hyperactivity Disorder
6	OCD	Obsessive-Compulsive Disorder
7	REM	Rapid Eye Movement
8	DWT	Discrete Wavelet Transform
9	LDA	Linear Discriminant Analysis
10	GSR	Galvanic Skin Response
11	HCI	Human Computer Interface
12	DIP	Dual in-line
13	SOIC	Small Outline Integrated Circuit
14	LOTO-CV	Leave One Trail Out Cross Validation
15	LOSO-CV	Leave One Subject Out Cross Validation
16	HPF	High Pass Filter

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

This project report examines the issues and difficulties of research project that was intended to evaluate the state of mind of a subject through Electroencephalogram (EEG). This work prompted the improvement of ongoing framework for investigation of brainwaves through EEG. EEG estimation is noninvasive, have a high affectability to get data about the inward (endogenous) changes of mind state, and offer a high time determination in the millisecond range. On account of the last property, these information are especially suited for studies on mind instruments of psychological passionate data handling which happens in the millisecond run. It has been outstanding that particular cortical and sub-cortical mind framework is used and have been separated by local electrical exercises as per the related emotional states. There are critical difficulties must be confronted for creating effective EEG signals for recognition of emotions, for example, (i) outlining a convention to stimulate one of a kind feeling than different feelings (ii) build up a proficient hardware and algorithm for expelling noises from the EEG signal. What's more, distinct exercises of the mind cause distinct EEG characteristics waves, it has been endeavored to make examination of this brain exercise related to attention and meditation easy by doing analyses of EEG signals.

1. CHAPTER - INTRODUCTION

1.1 Introduction

Automated examination of the physiological signals like EEG has turned out to be more broad amid the most recent 3 decades for advancement of Brain computer interfaces to incorporate regions such as lie recognition, stress & emotion estimation. So this spark enthusiasm for exploring whether a feeling can be perceived just by observing physiological reaction. Although emotional data could likewise be recovered from different modalities like subject's face appearances, content, motions, and so forth. Be that as it may, these can be deliberately adjusted. This prompted the advancement of emotion recognition strategies, human physiological signals, for example, heart rate, skin conductance, cardiovascular action, neural reactions (EEG), and so forth. Late investigates on the human EEG uncover that mind activity assumes a noteworthy part in the evaluation of emotions. Advance, perceiving emotional states from neural response is a successful method for executing BCIs. BCI frameworks make a correspondence channel between the mind and PC by procuring, examining and classifying neural exercises under specific simulations, and create control signals for existent globe applications in areas including clinic, psychiatry, security, military, law requirement and broadcast communications. Consequently, programmed emotion acknowledgment from EEG signals is acquiring more consideration these days. An EEG signal represents an electrical action of brain with its amplitude ranges from 10 to 100 microvolts whereas frequenct lies in the scope of 0 to 100Hz. Mind waves are described by six frequency sub groups, characterized as:

1.1.1) Infra Low [1]

Infra-Low brainwaves (otherwise called Slow Cortical Potentials), are thought to be the fundamental cortical rhythms that underlie our higher cerebrum functions. Next to no is thought about infra-low brainwaves. Their moderate nature makes them hard to identify and precisely measure, so few reviews have been finished. They seem to play a noteworthy part in cerebrum timing and system work.

- **Frequency range**: 0 Hz to 0.5 Hz (Slowest)

1.1.2) Delta waves [2]

These are the slowest traced cerebrum waves in individuals. They are discovered regularly in newborn children and youthful kids. [2] With the time as we grow, we tend to create less deltas still in deep sleep. They are related with the most profound levels of relaxation and remedial, mending sleep. They have likewise been observed to be required in insensible bodily tasks, for example, directing heart beat, digestion, etc. Sufficient creation of delta waves helps us feel totally revived after we wake up from a decent night rest. If in case Delta activity is not normal, an individual may encounter learning handicaps or experience issues keeping up cognizant mindfulness, (for example, in instances of brain damages).

- **Frequency range -** 0.5 Hz to 4 Hz
- **High -** Brain wounds, learning issues, not able to think, extreme ADHD
- **Very little -** Not able to revive body, not able to rejuvenate the brain, poor sleep
- **Optimal -** Immune system, normal mending, restorative or profound sleep
- **Increase delta waves -** Depressants, rest

1.1.3) Theta waves [2]

This specific frequency wave is included in daydreaming(inattention) and rest. Theta waves are associated with us encountering and feeling profound and crude emotions. A lot of theta movement may make individuals inclined to depression for a short period and may make these individuals "highly suggestible" in light of the way that they are in a profoundly relaxed, semi-sleep inducing state. Theta has its advantages of enhancing our instinct, imagination, and makes us feel more characteristic. It is additionally included in remedial sleep. For whatever length of time that theta isn't created in overabundance amid our waking hours, it is an exceptionally accommodating brain wave range.

- **Frequency range**: 4 Hz to 8 Hz (Slow)

- **High**: ADHD, depression, hyperactivity, impulsivity, non-attentiveness
- **Very little**: Anxiety, poor emotional awareness, stress
- **Optimal**: Creativity, emotional connection, instinct, relaxation
- **Increase theta waves**: Depressants

1.1.4) Alpha waves [2]

This frequency range crosses over the barrier between our cognizant speculation and subconscious personality. Or we can say alpha is having a frequency range between beta and theta wave. It helps a person to quiet down when vital and advances sentiments of profound relaxation. If the stress level increases then a phenomenon called "alpha blocking" may happen which includes extreme beta activity and almost no alpha. Production of alpha waves get "block" out by the waves called beta waves because we turn out to be excessively aroused.

- **Frequency range** - 8 Hz to 12 Hz (Moderate)
- **High** - Daydreaming, not able to focus, exessively relaxed
- **Very little** - Nervousness, extreme stress, insomnia, OCD
- **Optimal** - Relaxation
- **Increase alpha waves** - Alcohol, marijuana, relaxants, some anti-depressants

1.1.5) Beta waves [2]

These are called high frequency low amplitude mind waves that are normally watched while we are wakeful. They are included in cognizant thought, logical thinking, and have a tendency to have a stimulating effect. Having the perfect measure of beta waves enables us to concentrate and finish school or work-based responsibilities effortlessly. Having excessively beta may prompt us encountering intemperate anxiety or potentially tension. The higher beta frequencies are related with abnormal amounts of excitement. When a person drink caffeine, or uses another stimulant, there will be an automatic increment in his/her beta activity. Think about these as being quick cerebrum waves that a great many people display for the duration of the day so as to finish cognizant responsibilities, for example, significant thinking, reading, composing and socialization.

- **Frequency range** - 12 Hz to 30 Hz (High)
- **High** - Adrenaline, nervousness, high excitement, not able to relax, stress
- **Very little** - ADHD, daydreaming, depression, poor cognition
- **Optimal** - Conscious focus, memory, problem solving
- **Increase beta waves** - Coffee, energy drinks, other various stimulants

1.1.6) Gamma waves

These are included in processing large amount of tasks and additionally intellectual working. Gamma waves are imperative for learning, memory and data handling. It is believed that the 40 Hz gamma wave is essential for binding of person senses with respect to perception and is included in adapting new material. It has been figured out that people who are slow-witted and have learning incapability have a tendency to have bring down gamma activity than normal.

- **Frequency range**: 30 Hz to 120 Hz (Highest)
- **High**: nervousness, high excitement, stress
- **Very little**: ADHD, depression, learning disabilities
- **Optimal**: Binding senses, cognition, information processing, learning, perception, REM sleep
- **Increase gamma waves**: Meditation

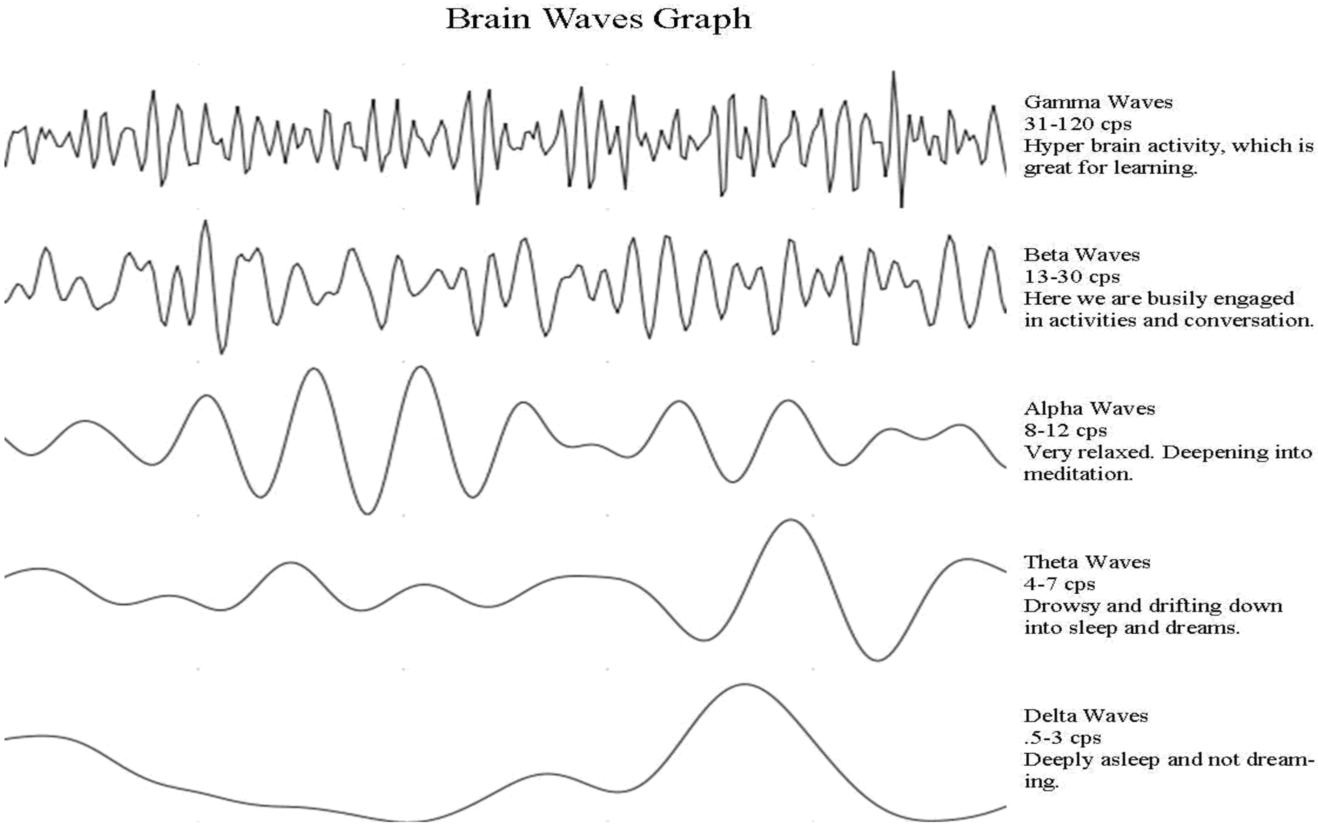

FIGURE 1.1: BRAIN WAVES GRAPH

The EEG signal frequency bands that are explained above are related with neural part and these are changed with change in the emotional environment. In this manner, by catching these varieties and investigating them, it is conceivable to portray the associated emotional state. Area of affective evaluating has been broadly investigated with regards to human neural reactions. Some beforehand distributed works uses measurable elements of EEG that automatically do the recognition of emotions, DWT and lifting based wavelet changes in combination with spatial filtering to take out emotion based features through EEG so as to characterize happiness, bitterness, disgust, and fear feelings. DWT based strategies are not all that most loved because of extensive list of features. Another research examines the utilization of optimization strategies involving diverse sizes of sliding windows, standardization approaches, filtering techniques and dimensionality depletion algorithms on time and frequency domain elements of EEG signals to differentiate wonderful, unbiased, and repulsive emotional states with the help of SVM. This is trailed by strategies that include the use of brief time Fourier Transform(FT) and Fast Fourier

Transform(FFT) to the obtained EEG signals to characterize sentiments of happiness, sorrowness, outrage, and joy/fear utilizing SVM but with less exactness. The combination of EEG with other physiological signals, for example, skin conductance, BVP and respiratory rate has been investigated effectively to characterize calm neutral and negative energized feelings utilizing GA and Elman neural system. The entire list of features involves linear elements of EEG in conjunction with disordered invariants like inexact entropy, fractal and correlation dimension. Encourage an arrangement of algorithms order human feelings by evaluating power spectrum density took after by the extraction and examination of five EEG control bands with the standardized EEG sub bands utilizing Bayesian system and SVM. The extraction strategies of linear features stifle the phase data associated to the morphology of non linear and non stationary EEG waves and in this manner are less exact. A gathering of analysts exhibited a method to identify and characterize emotions from human EEG signals with the help of higher order crossings examination and accomplished higher characterization rates to order the emotions into six classes. Another current research includes the utilization of higher order spectral elements of EEG to build up an emotional system that recognizes the stress with the help of LDA classifier and accomplished recognizable high accuracy. These most recent discoveries uncover the significance of higher order spectral examination in affective processing. The work that was done before for the most part includes the utilization of linear or nonlinear components of EEG. This venture proposes an ongoing convenient set up for recovery of attention and meditation states from human neural reactions by catching changes in EEG accomplished from corresponding lobes of cerebrum by using self made EEG machine using outer emotional stimulation.

1.2 Attention and Meditation

It is those behavioral and mental procedures which control the style and course of mindfulness. It is taking control by brain in clear and brilliant type of one out of what appear to be a few synchronous objects or lines of thoughts. Attention itself is constituted by one period of coherent mind activity in a cerebrum area and its content is constituted by another period of coherent action in an associated or adjacent cerebrum area. Two waves are called coherent when waves keep up a steady phase association with each other. By and large certain circulations of mind synchrony state the procedure of attention, and the content of attention are stated by other connecting dispersions of synchronous coherent action, which are however non-synchronous (but are still coherent) with first distribution. Centralization, focussing of cognizance is of its essence.

Meditation is a kind of activity that gives you profound rest. Meditation is an activity in which the person just sits and allows the mind to dissolve. At the point when the brain turns out to be free from unsettling, is quiet and tranquil and settled, meditation happens. For having more alpha brain waves it is necessary to be relaxed so one of the way is through meditation, controlled breathing and listening to certain kinds of music. Electrical cerebrum waves propose that mental action during meditation is alert and relaxed. Regardless of whether a man is rationally dynamic, resting or snoozing, the mind dependably has some level of electrical action. The review observed the frequency and area of electrical cerebrum waves using EEG (electroencephalography). EEG elecrodes were set in standard areas of the scalp. Subjects were made a request to rest, eyes shut and to meditate for at some point, in irregular request. The area and loads of slow to quick electrical mind waves (delta, theta, alpha, beta) give a decent sign of cerebrum activity. Alpha waves were in ample in the back parts of the cerebrum during meditation than during basic relaxation. They are normal for attentive rest. The aggregate of alpha waves increments when the mind unwinds from purposeful, objective arranged undertakings. This is an indication of profound relaxation, however it doesn't mean at all that the psyche is void.

1.3 Problem Statement

In the previous decades, the greater part of emotion recognition researches have just concentrated on using expressions that can be easily faked and these expressions are called facial expressions. As we know a person can easily hide his expressions and can easily change the speech tone& signals are not persistently accessible, & alter while using physiological signals, that happen constantly & it is very difficult to hide, for example, GSR, ECG and above all, EEG. Electroencephalogram is a signal that is generated and the cause for this are voltage fluctuations that occur in the cerebrum, & is the focal point of emotions. These are very much connected with movement in brain region that direct an individual attention, motivate an individual behaviour, and decide the importance of that is happening around us. It is connected with a group of structures in the focal point of cerebrum known as limbic system, that incorporates , thalamus, and hypothalamus and many more.

For emotion recognition there are various number of algorithms that exist. But the primary issue with these algorithms are there accuracy. As recognition of emotion is new to this world, a standard database of EEG signals for various emotions is required to set up, that could be utilized for more research on real time EEG-based emotion recognition. As of now, just restricted number of emotions could be detected. Research should be possible on more number of emotion recognition. Moreover, the vast majority of the emotion recognition algo's were produced for information processing that can be done off-line. In our project, we had focused on real time emotion recognition and its usages. The person emotions are perceived and pictured progressively on his/her avatar. In spite of the fact that in this venture, we depict independent execution of emotion recognition and its usages, it could be effortlessly stretched out for further use in collaborative environments/digital universe.

1.4 Objective

The main goal of HCI is to enhance the communications between the people and PCs. Since the greater part of the PCs not able to understand the person's emotion, some of the time they (PCs) can't react to the person's needs naturally and accurately. So, we have tried to detect emotions (attention and meditation) efficiently by working on alpha and beta waves to detect the state of mind of a person using self-made EEG machine which can be used in future to solve emotional problems of a person which leads to cases like divorce, depression etc. or to rather say it is done to cope up with stress.

1.5 Methodology

The procedure of emotion classification comprises of a few steps.

1. Participant is prepared for experiment using pre-requisite manual.

2. During experiment, the participant is asked to rest, blink eyes & read novel to obtain an emotion, and EEG signal is recorded in like manner.

3. Then objects that defile EEG signal are expelled. The analyses of this EEG data is done and required features are separated out.

Data obtained is utilized for analyzing attention and meditation state of a human being.

1.5.1 EEG Machine

1.5.1.1 Components

S. No.	Name of Item	Quantity	Cost
1	Instrumentation Amplifier Ad620An	1	700
2	Op Amp Tl082Cp	2	110
3	Op Amp LM741	1	10
4	Orange Drop Capacitor Kit	1	200
5	Din to Gold Cup EEG Electrodes	1	800
6	Nuprep EEG Skin Prep Gel	1	3690
7	Elifix Conductive EEG Paste, 3 Pack/8Oz	1	6658
8	Hi-Watt 9V Battery Set	1	234
9	Resistors	1	200
10	Breadboard - Full Size - 830 Tie-Points	1	345
11	Jumper Wire - 10 Male to Male + 10 Female to Female + 10 Male to Female	2 set	300
	Total		13247

TABLE 1.1: LIST AND COST OF COMPONENTS USED

Instrumentation Amplifier (AD620AN)

The low current noise of instrumental amplifier that is AD620 permits its utilization in EEG monitors there high source resistances of 1 MW or higher than this are normal. The AD620's that require low power, low supply voltage necessities, and also space saving 8-lead smaller than normal DIP and SOIC packet offerings settle on it a magnificent decision for battery controller data recorders.

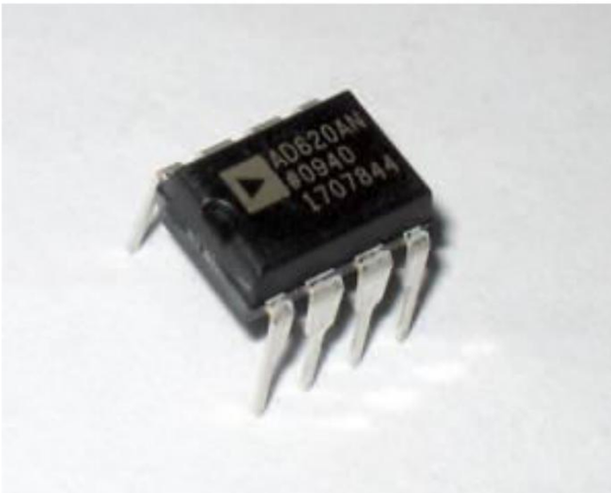

FIGURE 1.2: AD620AN IC

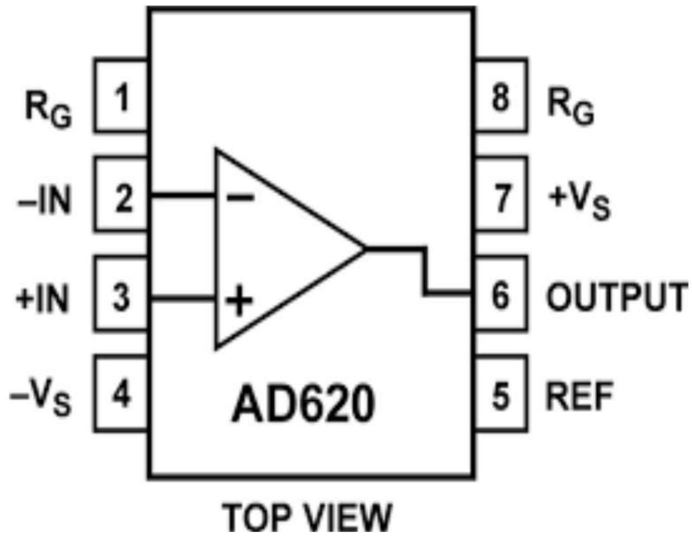

FIGURE 1.3: AD620AN PIN DIAGRAM

PIN NO	DESCRIPTION
1	Rg - Resistor Gain Setting
2	-IN - Input inverter
3	+IN – Non input Inverter
4	-Vs - -Ve Power Supply
5	REF – Reference
6	OUT – Output
7	+Vs - +Ve Power Supply
8	Rg - Resistor Gain Setting

TABLE 1.2: PIN USAGE AD620AN

BENEFITS	**REASONS**
Easy to use	• Gain set with one external resistor (gain range 1 to 10,000) • Large power supply range (±2.3 v to ±18 v) • Higher performance than three op amp instrumental amplifier designs • Available in 8-lead dip and SOIC packaging • Low power, 1.3 milli Ampere max supply
Low noise	• **9 nv/√hz**, @ 1 khz
Excellent direct current(dc) performance	• 50 µv max, input offset voltage • 0.6 µv/°c max, input offset drift • 1.0 na max, input bias current • 100 db min common-mode rejection ratio (g = 10)

TABLE 1.3: BENEFITS OF AD620AN

PARAMETER	**FIXED MAXIMUM RATINGS**
Supply Voltage	±18 V
Internal Power Dissipation	0. 650 MW
Storage Temperature Range	–65°C - +150°C

TABLE 1.4: FIXED PARAMATERS OF AD620AN

Operational Amplifier (TL082CP):

This device is cost efficient, have high speed, have double JFET input op-amp's with an inside trimmed input offset voltage. They need low supply current yet preserve a large gain bandwidth product and quick slew rate. Also, well coordinated high voltage JFET input device gives low input bias and offset currents. [52]

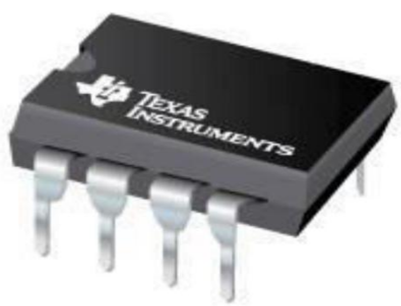

FIGURE 1.4: TL082CP DIAGRAM [51]

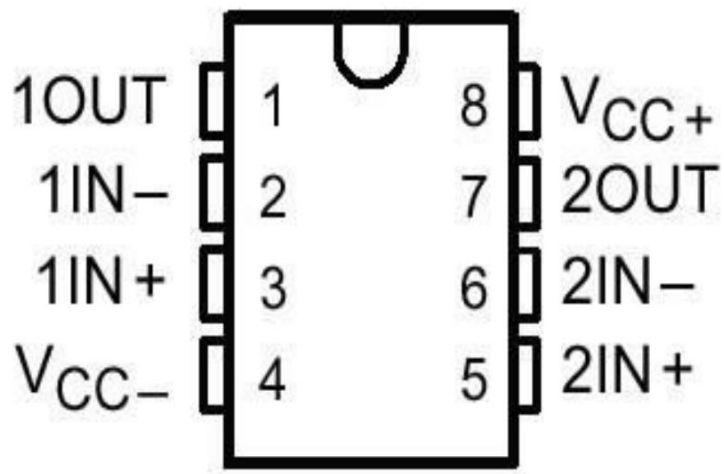

FIGURE 1.5: TL082CP PIN DIAGRAM[50]

NAME	NO	I/O	DESCRIPTION
INVERTING	2	I	Inverting signal input
NC	8	N/A	No Connect, should be left floating
NONINVERTING	3	I	Non-inverting signal input.
OFFSET NULL	1,5	I	Offset null pin used to remove the offset voltage and balance the input voltages.
OUTPUT	6	O	Amplified signal output
V+	7	I	+Ve supply voltage
V-	4	I	-Ve supply voltage

TABLE 1.5: TL082CP PIN USAGE

PARAMETER	**ABSOLUTE MAXIMUM RATINGS**
Supply Voltage	±18V
Storage Temperature Range	−65°C - +150°C
Input Voltage Range	±15V
Output Short Circuit Duration	Continuous
Lead Temp. (Soldering, 10 seconds)	260°C

TABLE 1.6: TL082CP ABSOLUTE PARAMETERS [53]

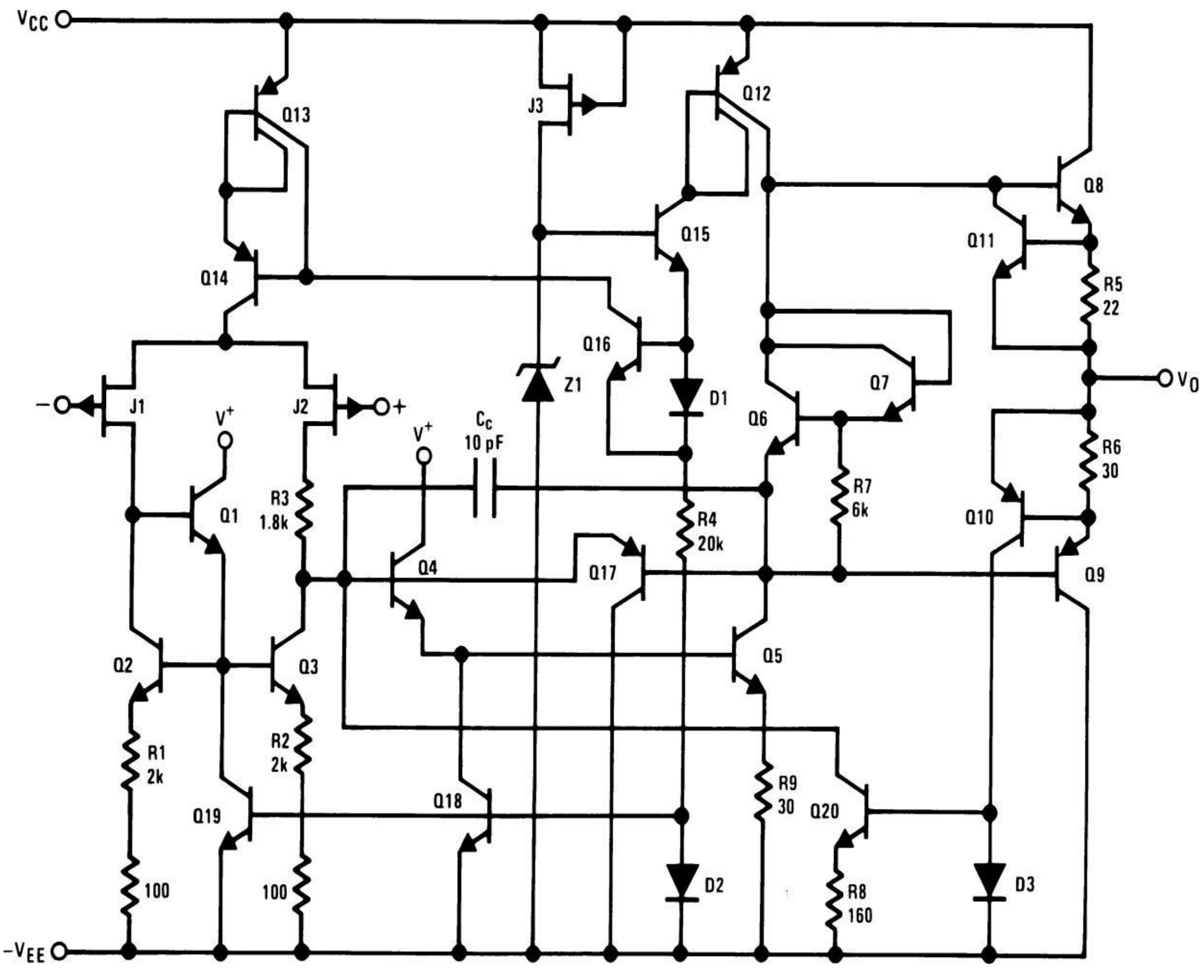

FIGURE 1.6: TL082CP INTERNAL CIRCUIT (DETAILED SCHEMATIC) [54]

BENEFITS	**REASONS**
Low Input Bias Current	50 Pa
Voltage	16Nv/√Hz
Low Input Noise Current	0.01 pA/√Hz
Wide Gain Bandwidth	4 MHz
Low Supply Current	3.6 mA
High Input Impedance	1012**Ω**
Low Total Harmonic Distortion	≤0.02%

TABLE 1.7: TL082CP BENEFITS[52]

Operational Amplifier (LM741):

The LM741 series are broadly useful op-amp's which highlight enhanced execution over industry norms like the LM709. The amplifiers present many features that make their application about foolproof.

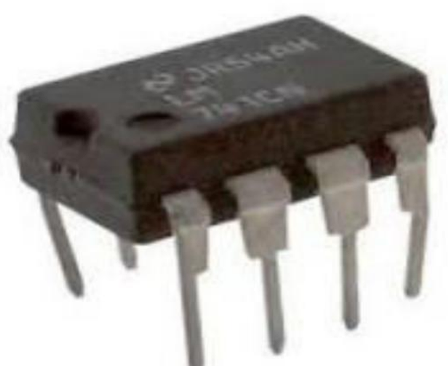

FIG 1.7 LM741CN[55]

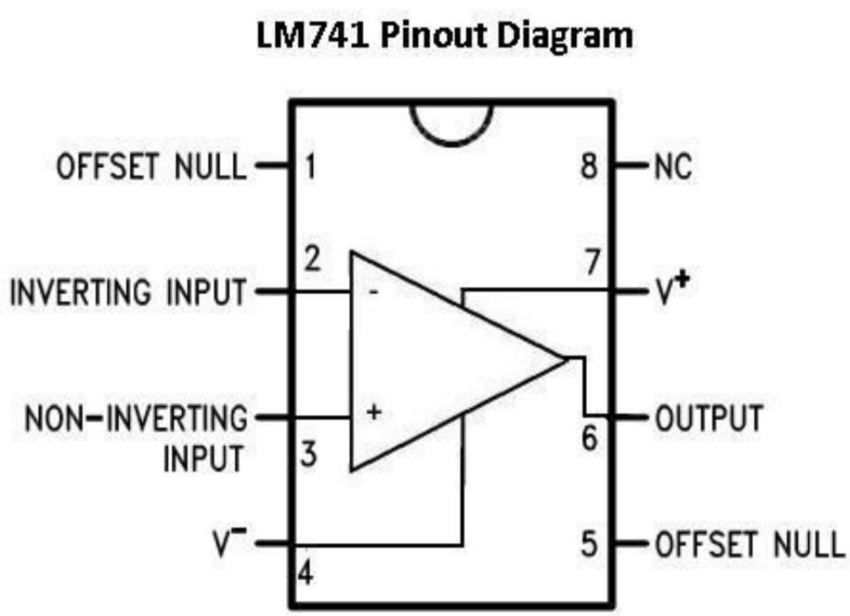

FIG1.8 LM741CN PIN DIAGRAM[55]

PIN NO	PIN NAME	DESCRIPTION
1,5	Offset Null	These are the pins where we insert voltage to if we wish to remove the offset voltage. This is used if we wish to completely balance the input voltages.
2	Inverting Input	This is where the +ve part of input signal that we desire to amplify goes if we wish our amplified signal inverted
3	Non-inverting Input	This is where the +ve part of input signal that we wish amplified goes if we wish our signal non-inverted.
4	V--	Where operational amplifier gets supplied with -ve DC voltage.
6	Output	Where the output, the amplified signal, comes out of IC
7	V+	Terminal which receives the +ve DC voltage.
8	NC	This pin is called Not Connected. It is not connected with anything and is left open.

1.8 TABLE: PIN USAGE LM741

Benefits [56]:

- Overload Protection on the Input and Output.
- No Latch-Up When the Common-Mode Range is exceeded

Applications [56]:

- Comparators
- Multi Vibrators
- DC Amplifiers
- Summing Amplifiers
- Integrator or Differentiators
- Active Filters

Arduino :

Arduino is an open source (whose code is easily available for free) platform that is based on easy to use software and hardware. Arduino boards can read inputs like light on sensor, a finger on button, a Twitter message - and provide an output for example, activate the engine, turn on the LED, publish some message on the web. We can guide Arduino board by sending set of guidelines to the microcontroller on board. For this we need the Arduino programming language (that is based on Wiring), and Arduino Software (IDE), that is based on Processing.

Arduino board designs make use of large variety of microcontrollers and in addition controllers. The boards are outfitted with sets of digital and analog input/output pins that might be interfaced to a variety of development boards (shields) and different circuits. The boards highlight serial interaction interfaces, involving Universal Serial Bus (USB) on a few models, which are likewise utilized for loading programs from PCs. The microcontrollers are normally programmed with the use of a dialect of features from the programming languages like C and C++. Notwithstanding utilizing traditional compiler tool chains Arduino project gives an integrated development environment (IDE) in view of Processing language project.

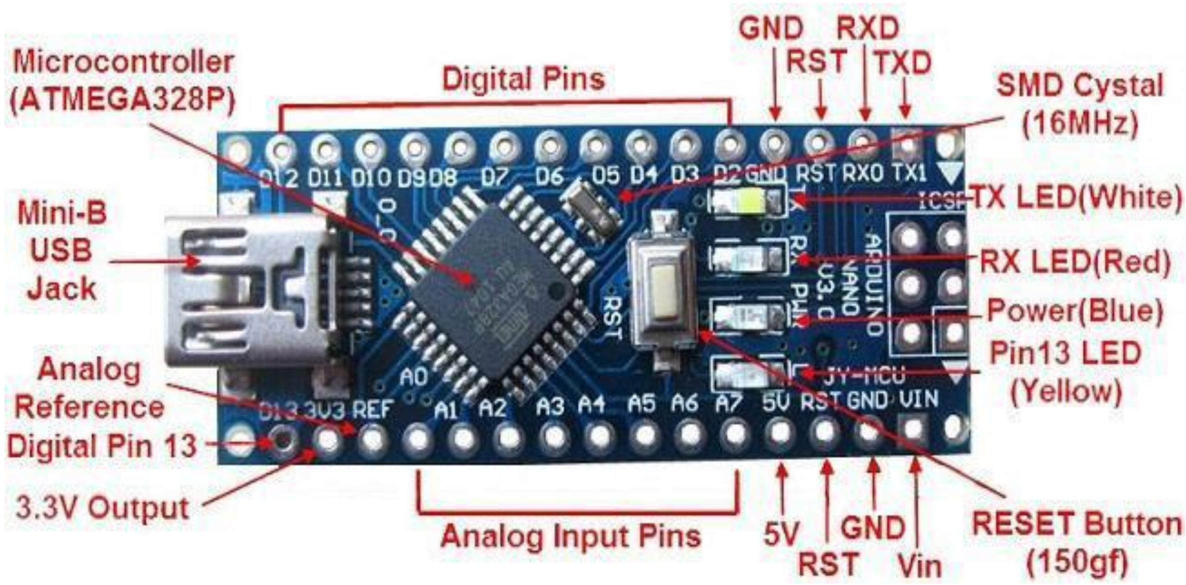

FIGURE 1.9

Orange Drop Capacitors [58]:

Gibson's 2014 model year guitars make use of Orange Drop capacitors, for this there is a justifiable reason motivation behind why Gibson picked them. It is a misinterpretation that all capacitors with a similar value are same; not exclusively can capacitor values differ as these capacitors come of te assembly line, capacitance can likewise shift with frequency,as well as with appied voltage, and temperature. On the off chance that our guitar make use of a low cost capacitor for its tone control and we think that our guitar sounds distinct under stage lights then when we are offstage, we are most likely right. Few ceramic capacitors are even somewhat microphonic, so they create sound when they subjected to high sound pressure levels.

The Orange Drop capacitor line presented in the '60s - the capacitors of the current time—with stability, resistance to temperature difference, absorb low moisture, amazing qualities in AC circuits, no microphonic, and other attractive characteristics. The outcome is - Orange Drop capacitors give the steadiness and accuracy—and along these lines, predictable tone—that experts anticipate.

Orange Drop capacitors have a good reputation for quality that demonstrated itself for near a large portion of a century. With a reputation like that, Orange Drop capacitors were reliable with Gibson's goal to make 2014 line of guitars and basses the best melodic instruments Gibson has ever delivered.

DIN Gold Cup Electrodes:

An electrode is called an electrical conductor that is used to get in touch with nonmetallic piece of a circuit (for example a semiconductor, an electrolyte, air). The word was authored by William Whewell at the demand of the researcher Michael Faraday from the Greek words elektron, which means amber(from where the word electricity is inferred), and hodos, a way.

FIGURE 1.10 EEG COLD CUP ELECTRODES

Electrodes are simply the things that a person place on himself/herself to identify electrical current; on account of OpenEEG, a person put them on his/her head to detect brainwaves. There are two fundamental types of electrodes that are Active and Passive.

1. **Active Electrodes** - These are electrodes with some inherent circuitry that is used for amplification of electrical current. This extraordinarily enhances the signal quality gotten by modular EEG and dodges the skin readiness and conductive glue required by typical passive electrodes. But this led to more work done than by passive electrodes but have a advantage that it produces much better results than passive electrodes.

2. **Passive Electrodes** - These are not having any inbuilt circuitry. But there is an assortment of various types.DIN Gold Cup Electrodes comes in the category of passive electrodes.

Nuprep EEG Skin Prep Gel:

FIGURE 1.11

Nuprep skin arrangement gel is applied on the skin before placing the electrode and is very beneficial as motion artifacts can change the readings, and when a decrease of skin impedance would upgrade a test outcome. Nuprep Skin Prep Gel viably brings impedance down to enhance your tracings. [61] To accomplish quality tracings, legitimate skin readiness at electrode site is essencial. Nuprep's mellow abrasiveness strips away the top most layer of skin where we have to place electrode and moistens the basic skin layer. By this activity it brings down the skin impedance with insignificant skin irritation and patient uneasiness. [62]

Nuprep Gel is significant at whatever point a decrease of skin impedance would upgrade execution of the monitoring electrode. Nuprep virtually disposes of issues, for example, diaphoresis and undesirable artifacts.

Applications for Nuprep gel[59]:

- EEG exams
- Stress tests
- Cardiac rehabilitation monitoring
- Sleep tests
- Audiology tests
- Intra-operative monitoring

Elifix Conductive Paste:

EEG Electrode glue, having low impedance and highly conductive gel, and is used to fix the electrodes on the skin.

FIGURE 1.12[62]

This paste can be applied on all surfaces where we can place electrodes. Time span of usability is 3 years unopened and 6 months after opening it. Conductive glue fill in as media to guarantee bringing down of contact impedance at cathode skin interface.

Applicable Instruments - All EEG and EP or EMG Instruments.

1.5.1.2 EEG Recording

The resolution is of 16 bits out of which 14 bits are valuable bits. Before doing recording we have place those electrodes on the scalp of a person for some amount of time so as to eliminate undesired emotions that arise due to awkward feelings that are mostly occur with whom we experiment for the first time. Then person is asked to remain still otherwise due to which undesired noise will come that we donot want as this will effect our readings. Now after all this we begun our recording and examination.

The EEG signal was filtered with the help of notch filter to delete the undesired **noise at 50 Hz and 60 Hz.**

Algorithm to classify two states Attention and Meditation

---

1) Capture packet using processing 2.2.6 which is input from audio jack of computer.
2) Check packet value
    a. If value = 0x00
        i. Drop packet
        ii. Loop to Step 1 until no data found
    b. Else
        i. Proceed to next step.
3) Decode code of packet based on predefined codes.
    a. If known code found
        i. Decode emotion
        ii. Loop to step 1 until no data found

b. Else

    i. Proceed to next step.

4) Analyze non-zero bits in packets.

5) Decode type of wave.

    a. If wave found

        i. Add to number of packets found of that wave

        ii. Show on screen

    b. Else

        i. Drop packet.

        ii. Add 1 to number of non-zero packets not analyzed

        iii. Loop to step 1 until no data found

6) Calculate mean values and other required parameters.

1.5.1.3 Feature Extraction

The EEG signal having a window of 1 second will be decayed to 5 frequency bands which are Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–16 Hz), Beta (16–32 Hz), and Gamma (32–64 Hz) by Wavelet Transform.Then the PSD from only two bands (Alpha and Beta) will be computed to the feature as the bands give more accurate results. We have used 2 channels and energy value is figured by the waveband circulation of EEG signals to deliver 2 features. In this review, the EEG signal data of the subjects that are tested was physically isolated into attention and meditation, and used to find out the recognition accuracy rate after finishing all the calculations and classifications with the help of the classifier.

1.5.1.4 Classification

Gaussian SVM is used to calculate the effectiveness for subject dependent and independent models with LOTO-CV and LOSO-CV. In LOTO-CV technique that uses 5 trials for testing, first trial will be test set & the left ones are training set. At that point training set is worked as a classification set & test set has been characterized by the use of this technique so as to assess accuracy. From that point onward, we will rehash the procedure utilizing dissimilar trials as test sets. The proper parameters will be set giving the best average out of 5 accuracies. In LOSO-CV strategy having 10 subjects where one subject will be considered as a test set and the rest are considered as training set. At that point the training set will be worked to be a characterization model and test set will be classified utilizing this model to assess exactness. From that point forward, we will rehash the procedure utilizing diverse subjects as test sets, until the entire of the 10 subjects have been considered as test sets. The fitting parameters are the set that will give the best average out of the 10 accuracies.

CHAPTER 2. LITERATURE SURVEY

Emotions play a crucial part in individuals' regular day to day existence. As indicated by hypotheses, emotions are the state of feeling that outcomes in physical and mental changes that control our conduct. Emotion recognition have expanded essentially in the course of recent decades with the commitment of many fields which incorporates brain science, neuroscience, medication, humanism, and considerably computer science.

In perceiving emotions, mind activity play a vital part in inspiration, discernment, cognition, consideration, learning and basic leadership. Evaluating emotions from the human cerebrum waves is very new and compelling zone of research.

EEG is identified with electric potential in various districts. This was considered to be one of the imperative methodology. In 1924 Hans Berger presented the idea of Electroencephalogram (EEG). The signals of EEG are recording utilizing electrical action of the cerebrum from the scalp. The EEG movement is very little, measured in miniaturized scale volts (mV). Mind cells persistently send messages to each other that can be gotten as little electrical impulses on scalp. The way toward getting and recording the impulses is called an EEG. An ordinary EEG implies that you have a simple pattern of brainwave movement. An unusual perusing implies that irregular examples of cerebrum movement are being delivered.

2.1 The review displayed in [22] presents the emotion recognition framework utilizing Electroencephalogram (EEG) signals, for investigating 4 emotional states, joy, relax, pitiful, and fear. The assessment of grouping, k-nearest neighbour (kNN) algo, and SVM were used the same as a classifier for feature extraction. Five right handed volunteers within the age group of 18-25 years participated in the study. A 128 channel electrical flag imaging framework. SCAN 4.2 software and an altered 64 channel Quick Cap with installed Ag/AgCl electrodes were utilized to procure the EEG signals. The test comes about show that normal test precision is 66.51% for grouping four emotional states acquired by utilizing frequency area components and SVM.

2.2 The EEG signals detected in human scalp were used to develop a real time emotion monitor showing emotional states of people, so that they can express their thoughts and feeling .The emotions were extracted from emotion indicators or indices, using relative power value from EEG. The study of emotions like happy, sad, fear, peace which were calculated using formulas as below;

For fear = relative power of Beta wave of T3/ relative power of Alpha wave of T3

For Sad =1/ relative power of Alpha wave of T3* relative power of Alpha wave of T5

For Peace= relative power of gamma wave of T5/ relative power of alpha wave of CP5

For Happy= 1/ relative power of Alpha wave of C4

The left temporal lobe decreased in alpha wave for negative emotions, were the alpha wave decreased in C4 in happy emotion, the increase of beta wave was observed in the left temporal lobe in fear emotional state and in the peace emotional state the gamma wave are seen to be increased in T5 [23].

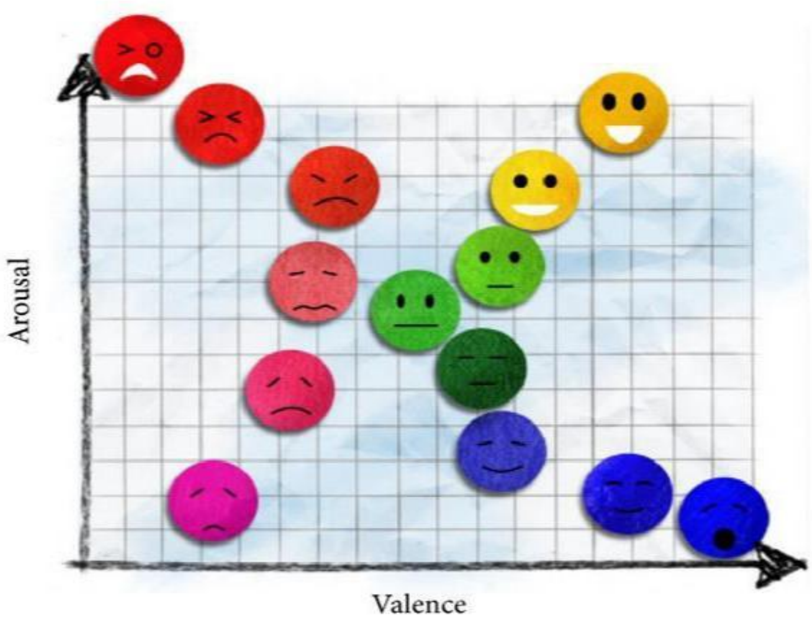

Figure 3: Dimensional model of emotion [14].

2.3 Mahalanobi Distance Based Classifier is able to determine EEG patterns by Using several EEG Electrodes- Fabio Babiloni et al. (2001) took 8 subjects and collected EEG signals on 4 electrodes, C3, P3, C4, P4.Each and every electrode is placed on the scalp according to 10-20 standard system of electrodes. Reduced set of recording electrodes were used by quadratic classifier based on MD classifier to detect EEG patterns so that emotions can be detected. Covariance and diagonal matrix were used by the classifier to detect imagination of movement. The accuracy obtained was 98% .By this accuracy it was made easy for Brain Computer Interface to use Mahalanobi distance classifier in which important factor was reduced set of recording electrodes [25].

2.4 The Real Time Based SVM for Recognition of Emotions with the help of EEG - Viet Hoang A**h et al. (2012) used Russell's** circumflex model in which two techniques were used.

Higuchi Fractal Dimension algo and SVM was also used the same as the classifier. One of the approach was the machine learning where EEG signals of each and every subject is taken under consideration and second one was the machine learning where EEG of each individual subject were taken. EEG signals of various subjects has distinct characteristics and due to this second approach was used instead of first approach that is of machine learning and five states of emotions were determined after calculating the average accuracy of 70.5%.The conclusion at the end was that the model should be improved since emotions and accuracy both were very small for real applications [26].

2.5 Towards Emotional alert Computing: It is the Integrated Approach proposed strategy for the grouping of neurophysiological information into four emotional states. These enthusiastic states were gathered amid uninvolved survey of passionate pictures chosen from IAPS. It embraces the independency of two emotive measurements. These are named as excitement and valence. For the judgment of enthusiastic states between EEG signals evoked by lovely and repulsive boosts, two stage order strategy was utilized, which likewise differ in their excitement/intensity levels. The arousal judgment was involved by first classification level. After performing arousal judgment, the valence judgment was applied. For the discrimination of emotions, there were two factors used named as the Mahalanobis Distance based classifier and Support Vector Machine. For the MD, gained classification rates were 79.5% and for SVM the gained rates were

81.3%.The first step towards number of applications including the sphere of human computer interaction was the robust classification of objective emotional measures. This procedure used the bidirectional cognitive model to get the provoked neurophysiological emotional reactions. These responses were classified by means of data mining methods [24].

2.6 The Database for Analysis of Emotion using Physiological Signal - Sander Koeltra et al. (2012) worked on multimodal data.32 participants were taken for analysis and they were asked to watch the 40 min music video and simultaneously EEG recording was going on. The video was rated according to valence arousal scale, likes/dislikes, dominance. Frontal face video was also recorded for 22 participants out of 32 [27].

2.7 Emotion Evaluation: excitement Evaluation Using EEG and Peripheral Physiological Signals - Guillaume Chanel et al. (2005) talked about emotion recognition using facial and verbal emotion with the help of EEG PET devices considering valence arousal dimensions.5 participants and 39 stimuli were taken and 4 emotions were categorized by splitting the data into training, testing and validation **[**28**].**

2.8 Extraction of Features using various strategies of EEG Signal for BCI Application -

Abdul Hameed Fatehi et al. (2011) studied the extraction of EEG signals.16 channels were used to gather EEG data with the help of mental and motor tasks. Features such as Time Analysis, Frequency Analysis, Time frequency analysis and space were extracted. Filtration was done with the help of LPF that is kept at 40 Hz and HPF with the frequency of 0.5 Hz. Artificial Neural Network was used to classify and the accuracy was 99%.Other classifiers used were FFT for time analysis, STFT for time frequency analysis [29].

2.9 The International Very Affective Image System: During the Study of Emotion

and Attention - Bradly M.M et al. (2005) talked about the images as stimuli from the IAPS that is known as the International Affective Image System. It helps in evoking the emotion.

Arousal, pleasure and dominance ratings are possible through these IAPS images. The IAPS was at present used in experimental examination of emotion through enabling the comparison of results of various studies in grouping to control emotions across psychosomatic and neuroscience research workshops [30].

2.10 Emotion recognition in the Loop from Mind Signals and Facial Pictures -

Aarman Savran et al. (2006) took a project to develop technique for multimodal emotion detection. Three modalities were taken where first is used for capturing brain signals with the help of fNIRS, second one is face video and third that is the last one is EEG signals that are captured from the EEG signals. The internal look of emotion generation processes is provided by EEG and fNIRS while the external look is provided by video sequence [31].

2.11 Extraction of Features from EEG machine for Emotion Classification -

Mandeep Singh et al. (2013) took the enterface data provided by Savran et al. (2006) [32] [33] [34] for 3 participants and performed classification along valence axis by using the naïve bayes classifier on the extracted ERP features. The overall accuracy achieved for

ERP feature was 56% and by changing the feature to STFT, effectiveness obtained was 51%. Same as with the PSD feature, effectiveness was 56% and after combining all the three features accuracy obtained was 64% which was comparatively high among all [35], while the overall accuracy achieved for 3 participants by using Artificial Neural Network was 76.59% [36].

2.12 Emotion Recognition through Facial Expressions utilizing Multilevel HMM - This work concentrates on natural facial appearance recognition from live video input utilizing transient signals. Techniques for utilizing transient data have been widely investigated for speech recognition usages. Among these techniques is layout coordinating utilizing dynamic programming strategies and shrouded Markov models (HMM). The curiosity of this engineering is that both division and detection of facial expressions are done consequently utilizing a multilevel HMM design while expanding the separation power between the diverse classes. This framework investigates individual dependent and person-independent detection of expressions.

2.13 EEG-Based Emotion Detection through Listening of Music (Yuan-Pin Lin, Chi-Hng Wang, Tazyy-Ping Jung): This work have made use of machine learning algorithm to categorize emotional state of a person during music listening. Classifier used to is SVM(support vector machine) and MLP with classification accuracy 82%.A machine learning approach is used to categorize 4 music persuaded emotional states is projected and tested in this learning, that might gives you a distinct point of view and new approaches into listening of music and emotion responses[42].

3. CHAPTER - SYSTEM DEVELOPMENT

Modular design, or "modularity in design", is a design approach that subdivides a system into smaller parts called modules or skids, that can be independently created and then used in different systems. A modular system can be characterized by functional partitioning into discrete scalable, reusable modules, rigorous use of well-defined modular interfaces, and making use of industry standards for interfaces.

Besides reduction in cost (due to less customization, and shorter learning time), and flexibility in design, modularity offers other benefits such as augmentation (adding new solution by merely plugging in a new module), and exclusion. Examples of modular systems are cars, computers, process systems, solar panels and wind turbines, elevators and modular buildings.

Our EEG machine is built on the concept of modular design and development to ease the process of development and debugging. It is built in 6 stages which are explained below.

Stage 1st –(AD620AN) Instrumentation Amplifier

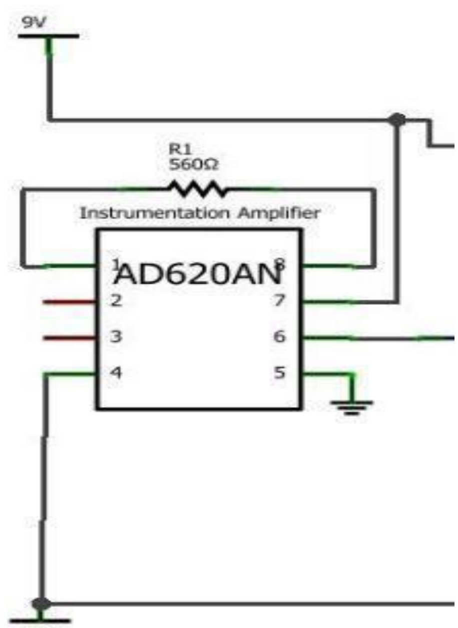

FIGURE 3.1

An instrumentation amplifier(AD620AN) that we have used takes two input voltages, and we get the output by subtracting these two inputs that are multiplied by some gain factor, G. It is sort of differential amplifier that has equipped with the input input buffer amplifiers, that wipe out the requirement for input impedance matching & makes amplifier especially reasonable for the use in estimation & test equipment. Extra attributes incorporate low DC balance, low drift, low noise, and large input impedances. These are utilized where we require high accuracy and stableness of circuit in both the short term and long term. These, be that as it may, are not great. On real amplifiers, outcome is marginally skewed if both the input voltages are balanced the same by some sum. A flawless amplifier would take as sources of inputs 2.1 V & 2.2 V, & output 0.1 V*G. A genuine one is impacted by this regular offset, & would change output somewhat as needs be. The CMRR is an esteem given to the amplifier that compares to how well it overlooks the basic offset between the data sources. A higher the CMRR, better it will be, & will output something nearer to what an impeccable amplifier would.

Why AD620AN? Instrumentation amplifier can be made by our own this can be done usually with 3 op-amps, but unless it made with correct resistors, it will definitely suffer from low CMRR. As the Low CMRR is explained above that will not neglect offsets accurately.

By the use of a chip of instrumentation amplifier that is AD620AN, then the gain is altered by changing the value of resistor b/w the pin 1 & 8. After the analyses that is done from datasheet of chip, it is seen that using this chip the formula for gain is

$$G = 1 + 49{,}400 / R \text{ (in } \Omega)$$

$$G= 1 + 49{,}400 / 560 \ (\Omega)$$

$$G=89.2 \text{ (approximately)}$$

this equates to the gain of 89.2 with 560-Ω resistor. This is the good number to get out data into not-miniscule range, we will find out a way to adjust the gain on fly after some later point of time. After analyzing datasheet, it is also clear that on the actual circuit, active electrodes (ones those are not the ground electrode) are connected to pin 2 & 3 (-IN and +IN).

Stage 2nd - 60 Hz Notch Filter

In signal processing, a band-stop filter or band-rejection filter is a filter that passes most frequencies unaltered, but attenuates those in a specific range to very low levels. It is the opposite of a band-pass filter. A notch filter is a band-stop filter with a narrow stopband (high Q factor).

Narrow notch filters (optical) are used in Raman spectroscopy, live sound reproduction (public address systems, or PA systems) and in instrument amplifiers (especially amplifiers or preamplifiers for acoustic instruments such as acoustic guitar, mandolin, bass instrument amplifier, etc.) to reduce or prevent audio feedback, while having little noticeable effect on the rest of the frequency spectrum (electronic or software filters). Other names include 'band limit filter', 'T-notch filter', 'band-elimination filter', and 'band-reject filter'.

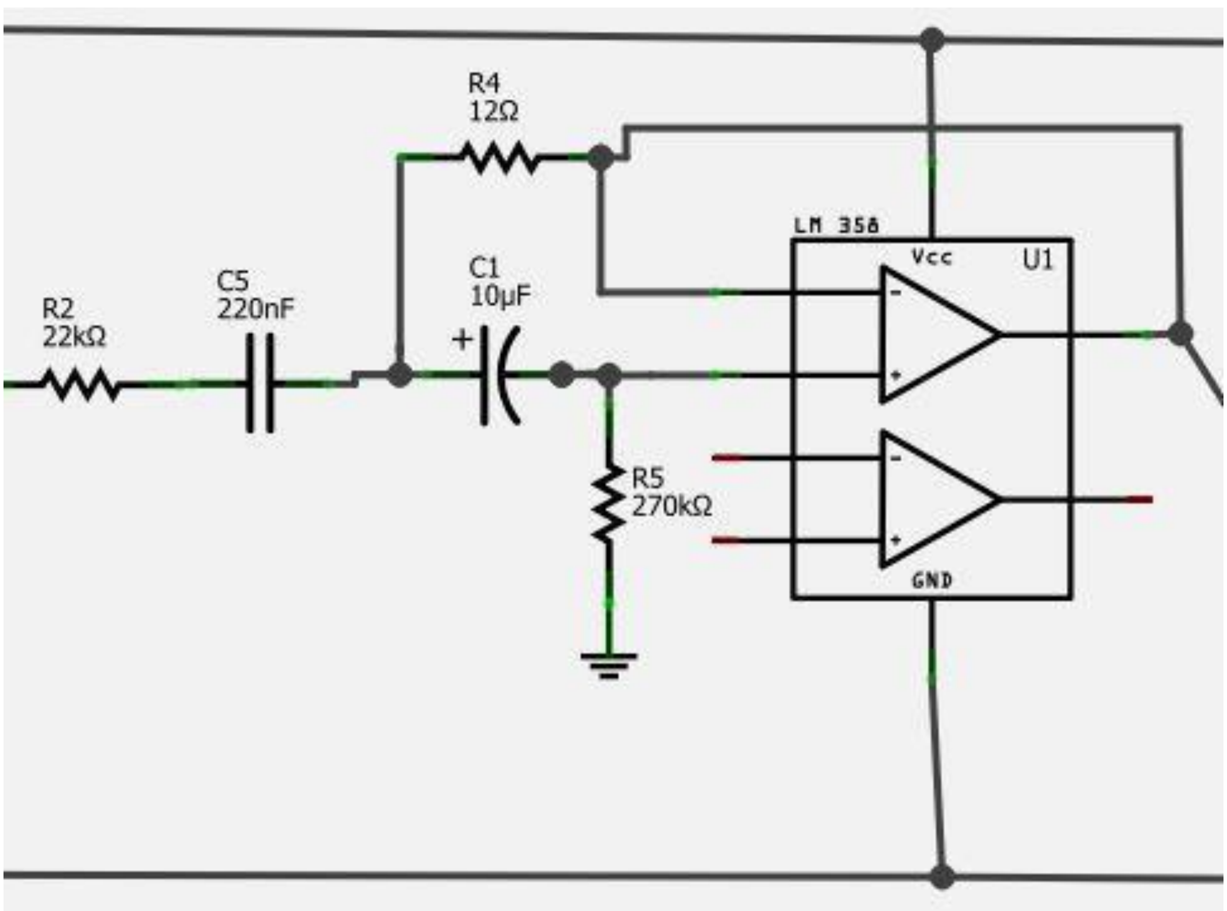

FIGURE 3.2

As interference occurs because of the power line & because of this we get most of noise that is centered at 50 Hz. Circuit keeps experiences the noise after the usage of batteries too that are basically used to power our circuit. So to remove this we have used 2 Notch filters that diminishes the gain by about 1 particular frequency. So we have used one of them in the second stage so as to reduce much noise as of now before applying any more gain to our circuit and used one of them at the end of the circuit to remove all the interferences we have come across after the first noch filter that we have applied in 2nd stage.

If any of the alterations are done in 10 Ω resistor then it is one of the most sensitive filter we have come across. So we have taken a reading after 1st stage to check whether the notch is there at 50 Hz i.e. at end of IA and then this process is done again after passing the signal through notch filter. By doing this we have significantly reduced the amplitude of 50 Hz frequency band.

Stage 3rd - 7Hz High Pass Filter

A high-pass filter is an electronic filter that passes signals with a frequency higher than a certain cutoff frequency and attenuates signals with frequencies lower than the cutoff frequency. These filters have many uses, such as blocking DC from circuitry sensitive to non-zero average voltages or radio frequency devices. They can also be used in conjunction with a low-pass filter to produce a bandpass filter.

Considering input EEG signal as discreet (sampled signal), The following pseudocode algorithm will simulate the effect of a high-pass filter on a series of digital samples:

```
// Return RC high-pass filter output samples, given input samples,
// time interval dt, and time constant RC
function highpass(real[0..n] x, real dt, real RC)
    var real[0..n] y
    var real α := RC / (RC + dt)
    y[0] := x[0]
    for i from 1 to n
        y[i] := α * y[i-1] + α * (x[i] - x[i-1])
```

return y

High-pass filters have large number of applications. These filters are utilized as a part of audio-crossover to direct the frequencies that are high to the tweeter and at the same time as attenuating the bass signals that can interfere with, or harm, the speaker.

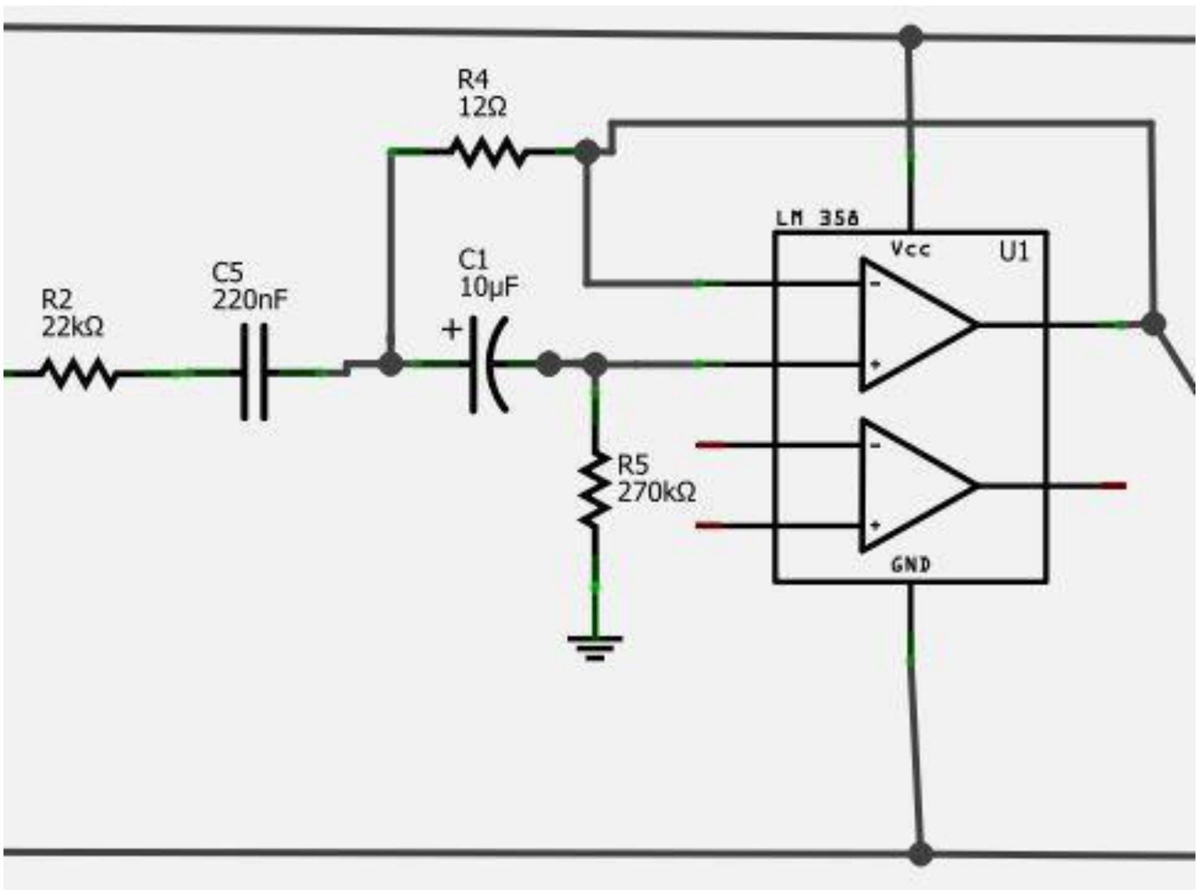

FIGURE 3.3

As we are doing the measurement of data over the skin, our final data that will be obtained will likewise contain the voltage from our galvanic skin reaction over our head. This will darken the cerebrum data we need, & as this obstruction is basically low frequency, it can be reasonably effortlessly filtered through with the HPF. The exchange off doing this is that we additionally filter through a ton of gamma/delta wave data (the cerebrum waves are around 8 Hz & less), yet as our fundamental concentration is alpha/beta wave checking, this isn't quite a bit of an issue.

This HPF filter is a 2-pole HPF having a cutoff frequency of 7.23Hz. A filter having cutoff frequency of 7.23Hz implies that at this frequency, circuit will output data that is lessened to around 71% of its initial value. As it is HPF, so the frequencies that are over this cutoff will approach a pick up of 1, while the frequencies that are beneath this cutoff will be consistently decreased. The filter that is having 2 poles implies that in the area beneath cutoff frequency, gain tumbles off considerably speedier than a less complex resistor/capacitor circuit. All the more particularly, in this circuit, our double pole structure lessens the data by an element of around 56 when it gets to 1 Hz, while a single pole would just diminish it by a component of around 7.5.

Stage 4th - 31Hz Low Pass Filter

In a low-pass RC channel for voltage signals, frequencies with a high value in input signal are constricted, however the filter is having a little lessening beneath the cutoff frequency found out by RC time constant. LPFs are utilized on contributions to subwoofers and different sorts of loud speakers, so as to block the high pitch voice that they can't effectively imitate. An ideal LPF totally dispenses with all frequencies over the cutoff frequency while passing those underneath unaltered. Real filters for continuous applications inexact the ideal filter by truncating and windowing the interminable impulse reaction to make a limited impulse response. There are a wide range of kinds of filter circuits, with various responses to altering frequency.

- A 1st order filter, for instance, decreases signal amplitude by half (so control diminishes by a component of 4, or 6 dB), each time the frequency duplicates (goes up by one octave), all the more unequivocally, the power move off methodologies 20 dB for every decade in the point of confinement of high frequency.

- A 2nd order filter lessens high valued frequencies all the more steeply. The Bode plot for this type of a channel takes after that of 1st order filter, with the exception of that it tumbles off more rapidly.

- 3rd or higher order filters are characterized comparatively. When all is said in done, the last rate of power move off for order n all-pole filter is 6ndB for each octave (that is, 20ndB for every decade).

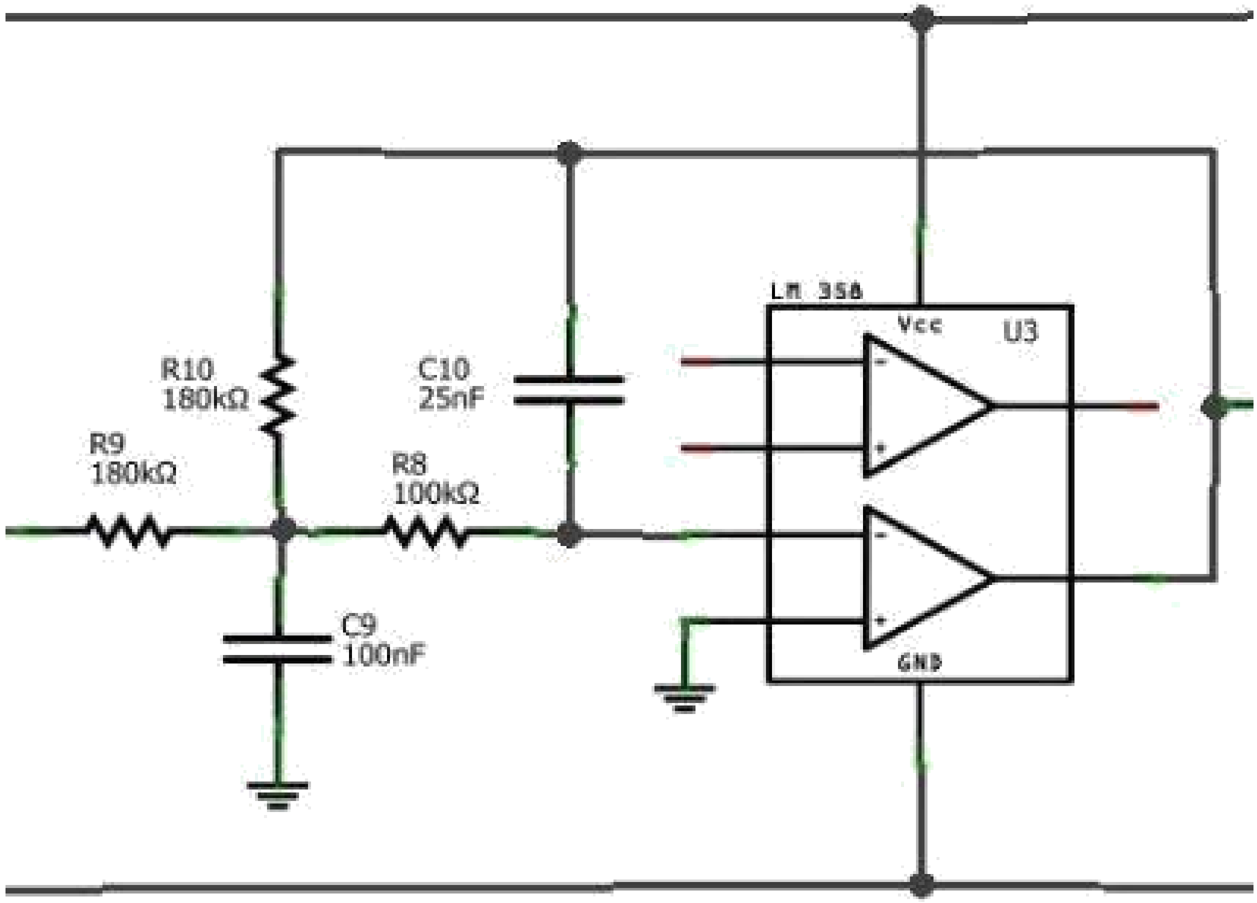

FIGURE 3.4

Now the next step is, we wish to filter out the data that is above the frequencies in which we are concerned in. More exclusively, as the wave information of beta stops out at 30Hz frequency, so we wish to get out of anything that is above that, as if we combine this it can put in a good amount of noise that we do not want to effect our data. This stage has the gain of 0.71 at the 31.23 Hz frequency, and from there it has diminished at rate by 300 Hz & attenuated our data around factor of 100.

Stage 5th - 1 Hz High Pass Filter and Gain of 83-455

The sum by which the approaching signal is amplified is given in unit called decibels (dB). Voltage get doubled when it equates to each gain of 6DB. The ideal measure of voltage gain can change contingent upon a couple components. Using receiver with inadequately executed preamplifier yields for instance can be an issue when coupled to a powerful amplifier with generally low voltage gain & thusly a high input affectability, that is a measure of voltage required from preamplifier to drive amplifier to full unclipped power.

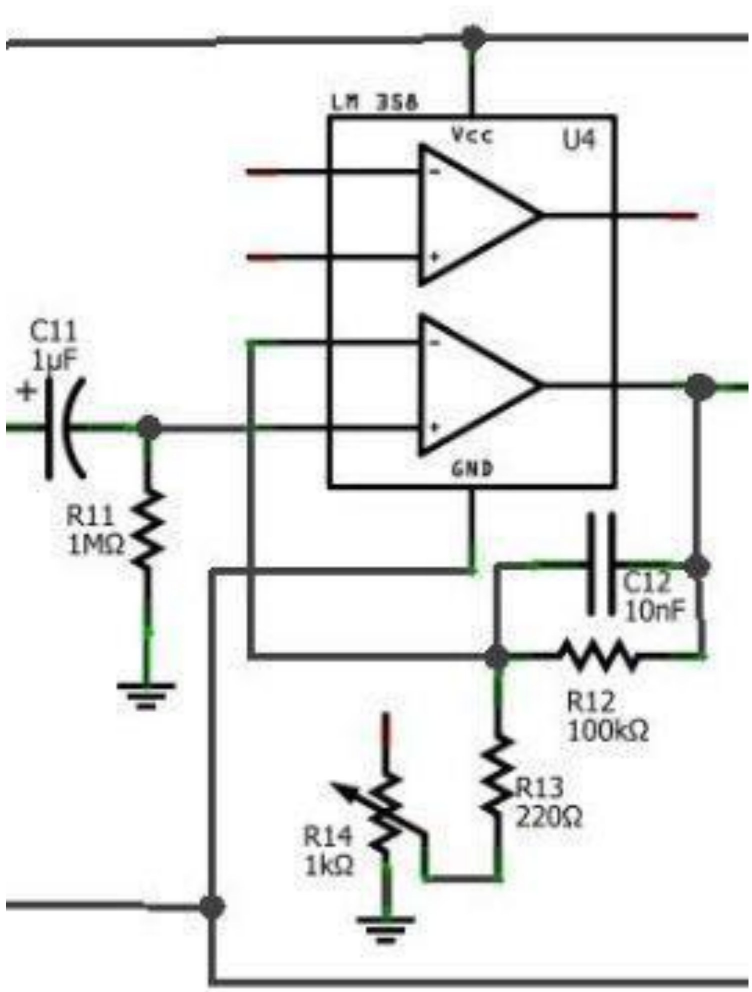

FIGURE 3.5

In the starting of this 5th stage circuit, it contains the quick HPF having the cutoff frequency of 1Hz

$$Fc = 1/(2*\pi*R11*C11)$$

Only for somewhat extra attenuation of the noise that we do not need . On other end, additional filtering of frequencies that are high are provided by the registers and capacitors that are in parallel on a LPF.

$$Fc = 1/(2*\pi*10 \text{ nF}*100 \text{ k}\Omega) = 160\text{Hz}$$

The main reason of the module, however, lies under this, with 220 ohm resistor & potentiometer. This operational amplifier is non-inverting, & as a result has the gain of

$$G = 1 + R12/(R13+R14) \ldots\ldots\ldots\ldots..(1)$$

(neglecting 10 nF capacitor, as it is of a quite small value & won't add a lot to the gain). The potentiometer is the variable resistor as when an input is connected to first pin & an output to the second one, turning the wiper change its resistance linearly b/w 0 & 1000 Ωs. This tells us that when potentiometer is turned all the way to left then the gain of the circuit is 455 where value of R12 is 100k, R13=220 and R14=0 (get the result by using (1) equation)

- Potentiometer is turned all the way to right then the gain is 83 where value of R12 is 100k, R13=220 and R14=1000 (get the result by using (1) equation)

So the results we get are on top of 89.2x gain from IA. As Amplitude of Alpha wave alters from individual to individual, approx. by 10 - 30 µV. Utilizing the value 20 µV, states that the ending voltage reading ranges from .148 V to .81172 V. After asking the person to not to move we started taking our readings with the help of potentiometer , while doing all this care must be taken that voltages should not fluctuate over 1V otherwise results will get affected. We shouldnot need to maximize this as all this happen without clipping and if tried to do this then error will definetly increase that will incur from reading data digitally into the PC.

Stage 6th - Another 60Hz Notch Filter (and into the computer)

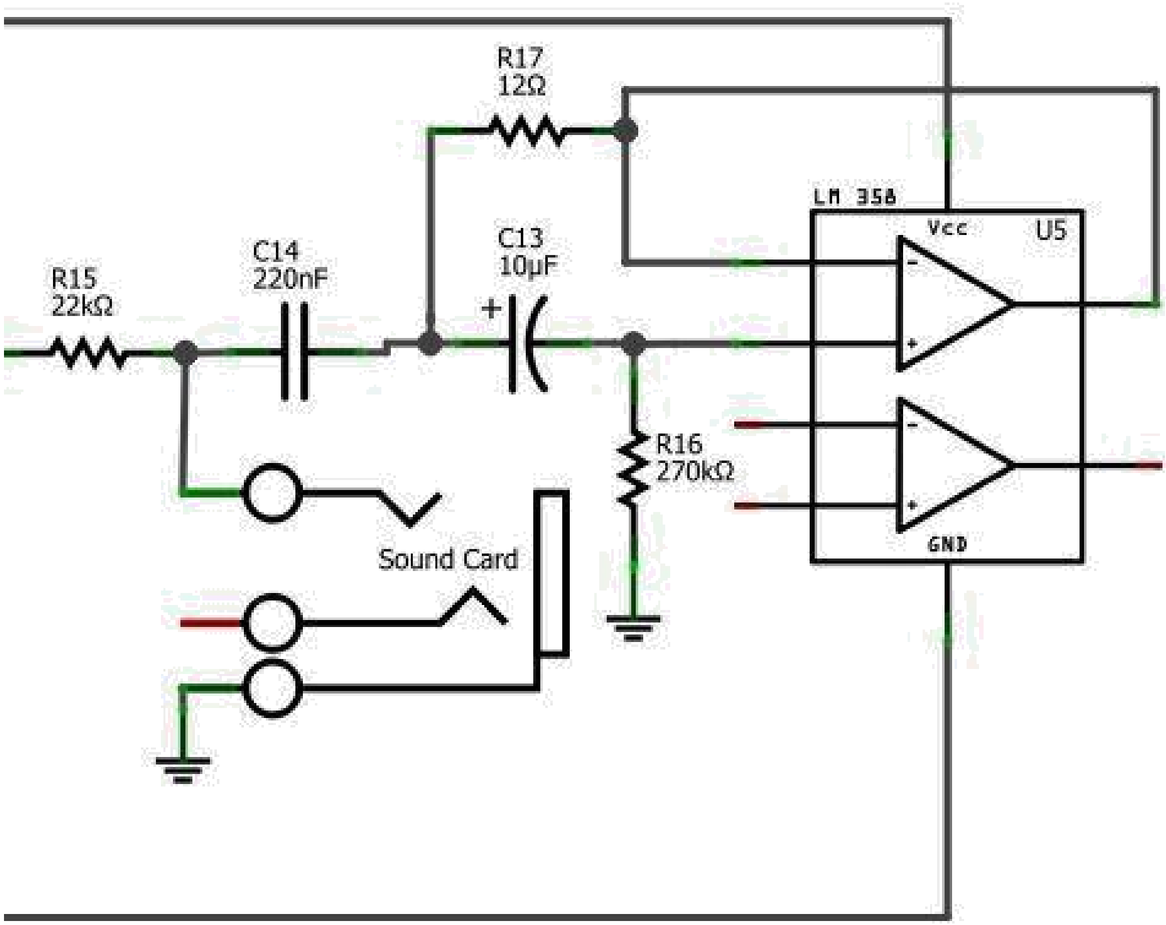

FIGURE 3.6

Indeed, after going across all the above stages we still left with some noise that incurred at 50 Hz. So to settle this, we have used the 2nd notch filter that we had discussed above centered at 50 Hz. After this too we remain with very little noise that is removed after the data is send into the PC with the help of software.

For sending the data into PC we have used the cable i.e. 3.5 mm male-to-male. And on cable, the initial 2 notches are left & right channels, & one uttermost down is ground.

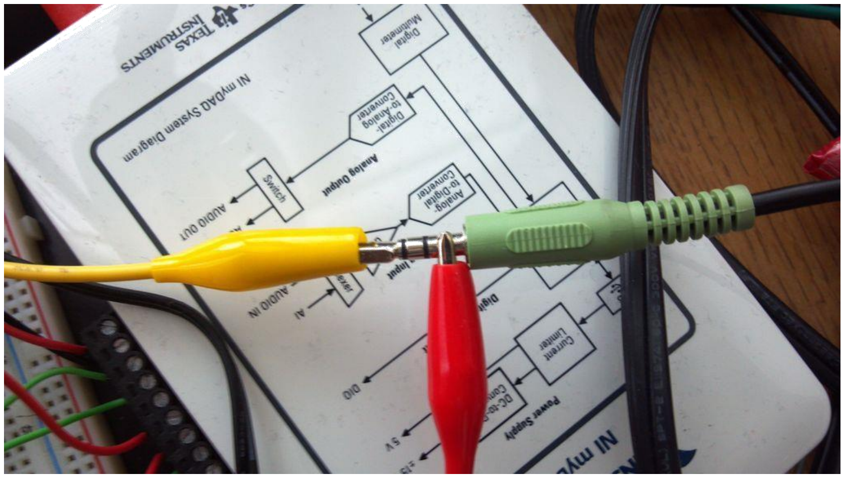

FIGURE 3.7

As appeared in photo, you ought to associate the end of cable b/w 22k resistor & 220 nF capacitor, & ground line of our circuit is associated to base cable - a similar line we associated our ground electrode to red alligator clip that is shown in picture. And now we associated other end of this cable into microphone port of PC.

Proper placement of electrodes

The 10-20 system is an universally recognized technique that is used to apply the electrodes in the exact location of scalp during EEG test or some experiment. Here the “10” & “20” represent actual distances b/w consecutive electrodes that are 10% or 20% of total right-left and front-back of head. Each & every site is having a letter & a number to get the lobe & hemisphere location. There are some standarised conventions that are – F- (Frontal), T- (Temporal), C- (Central*), P- (Parietal), O- (Occipital). Here Central lobe actually not exists. Its purpose is only for identification.

Indeed, even and odd numbers less than ten refer to location of electrode om correct hemisphere and on left hemisphere respectively.

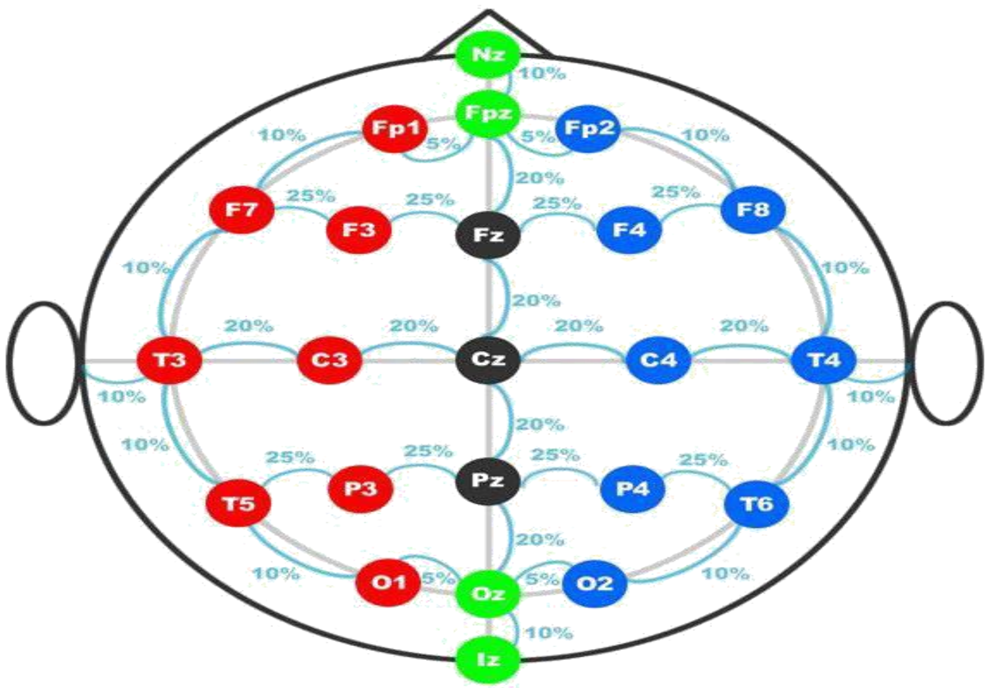

FIGURE 3.8

Steps to place electrodes:

1. Firstly measuring tape is taken whose centimeter sde is used. Then take the measurement of the line that is in the center of the scalp that is from Nasion part(bridge of nose) to the Inion part(occipital preberance), then calculate the complete length.
2. Take the Measurement & mark 50% of the total length. This is called preliminary Cz mark.
3. Take the Measurement and mark 10% upwards from Nasion and 10% upwards from Inion. These are called preliminary marks of Fpz and Oz.
4. Mark 20% either from first mark of Fpz or Cz. These are called preliminary marks of Fz and Pz.
5. Take the Measurement from the preauricular to preauricular point. Calmly run your finger up and down only anterior to ear, the indentation above zygomatic notch will be

easily identified. To find the correct location, open your mouth slightly. Then note total length.

6. Take the Measurement and mark 50% of the total. At the intersection with 50% mark That was found previously from Nasion to Inion is the true Cz mark.
7. Take the Measurement and mark 10% upwards from pre-auricular points. These points are called preliminary marks of T3 & T4.
8. Take the Measurement from the first mark of T3 to Cz. Note down the total length. Take the Measurement from the first mark of T4 to Cz. Note down the total length.
9. Take the Measurement and mark 50% of totals in previous step. These marks are the preliminary marks of C3 and C4.
10. Draw the cross-section mark on Fpz. This is a true Fpz mark.
11. Encircle the measurable tape accross our 10% Fpz mark and 10% Oz mark at back of head. Note down total circumference of head that is found out. Measure 50% of total circumference from Fpz to the backside of the head. At cross-section with the preliminary Oz mark is the true Oz mark.
12. Take the Measurement & mark 5% of total circumference to left & right of Oz. These marks will be the true marks of O1 & O2.
13. Take the Measurement and mark 5% of total circumference to left & right of Fpz. These marks will be the true Fp1 & Fp2 marks.
14. Take the Measurement and mark 10% downwards from Fp1 & Fp2. These marks are the marks for F7 & F8.
15. Take the Measurement from F7 to F8 & note down the distance.
16. Take the Measurement & mark half of distance b/w F7 & F8. At the intersection with the preliminary Fz mark is true mark for Fz.
17. Take the Measurement from F7 to Fz, note down the distance. Take the Measurement from F8 to Fz, then note down the distance.
18. Take the Measurement and mark half of distance b/w F7 to Fz and F8 to Fz. These are the preliminary marks for F3 & F4.

19. Take the Measurement and mark 20% of Nasion-Inion distance from the FP1 to F3. At the intersection point, will be the true F3 mark. Take the Measurement & mark 20% of Nasion-Inion distance from FP2 to F4. At intersection point, will be the true F4 mark.

20. Take the Measurement from the Fp1 to O1, so to obtain the preliminary mark of C3. Take the Measurement from Fp2 to O2 so as to obtain the preliminary mark of C3.

21. Take the Measurement and mark half of distance from Fp1 to O1. There first & second marks intersect will be the true C3. Take the Measurement & mark half of distance from Fp2 to O2. There first & second marks intersect will be the true C4.

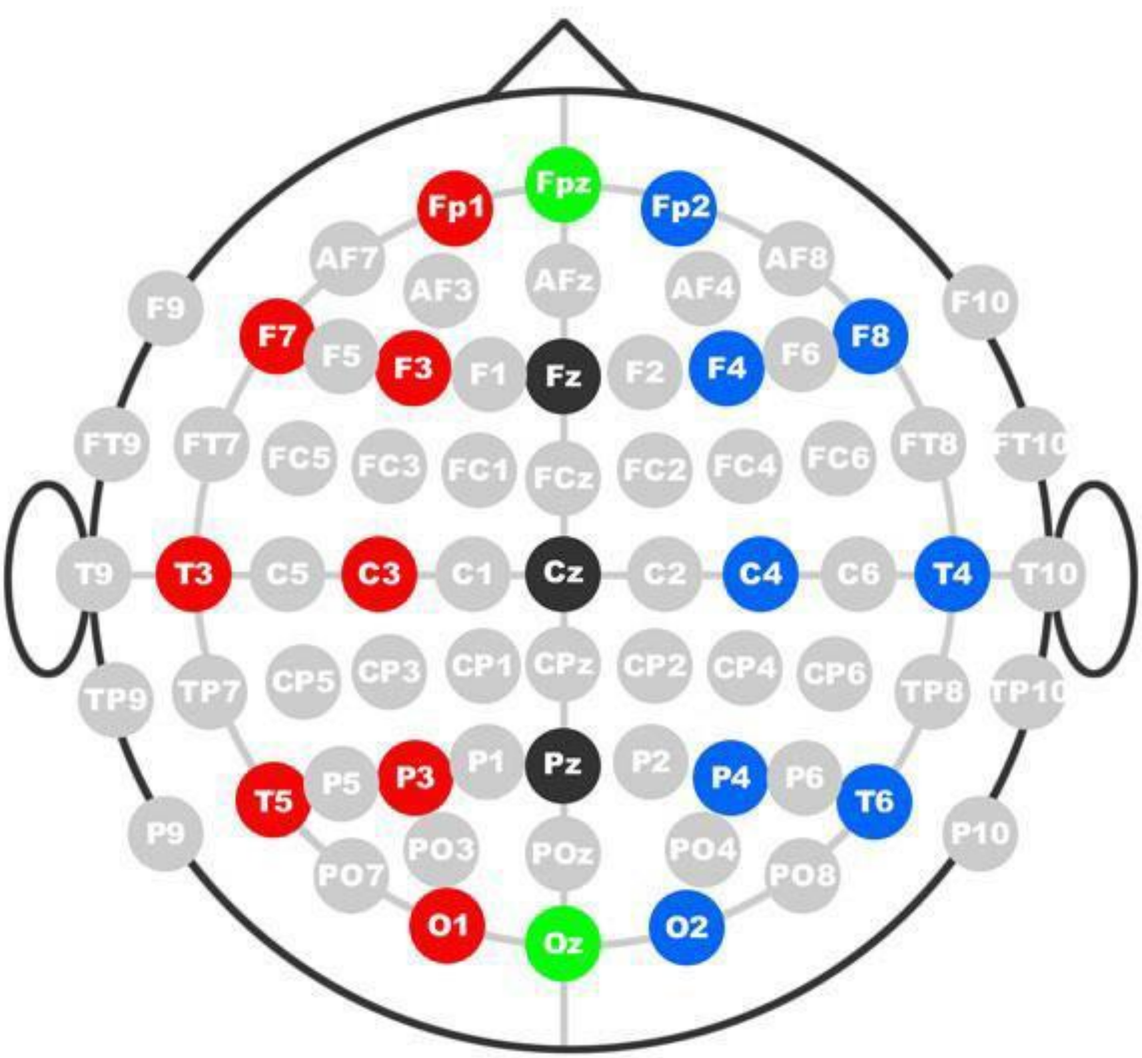

FIGURE 3.9

4. CHAPTER – PERFORMANCE ANALYSIS

Circuit Analysis

Machine is checked at various stages to give different outputs which are checked against theoretical values calculated from good performance and reliability of results.

Outputs were modelled using Lab View IDE. Screenshots of the output are attached below.

At stage 2 of machine i.e. 50 Hz Notch Filter.

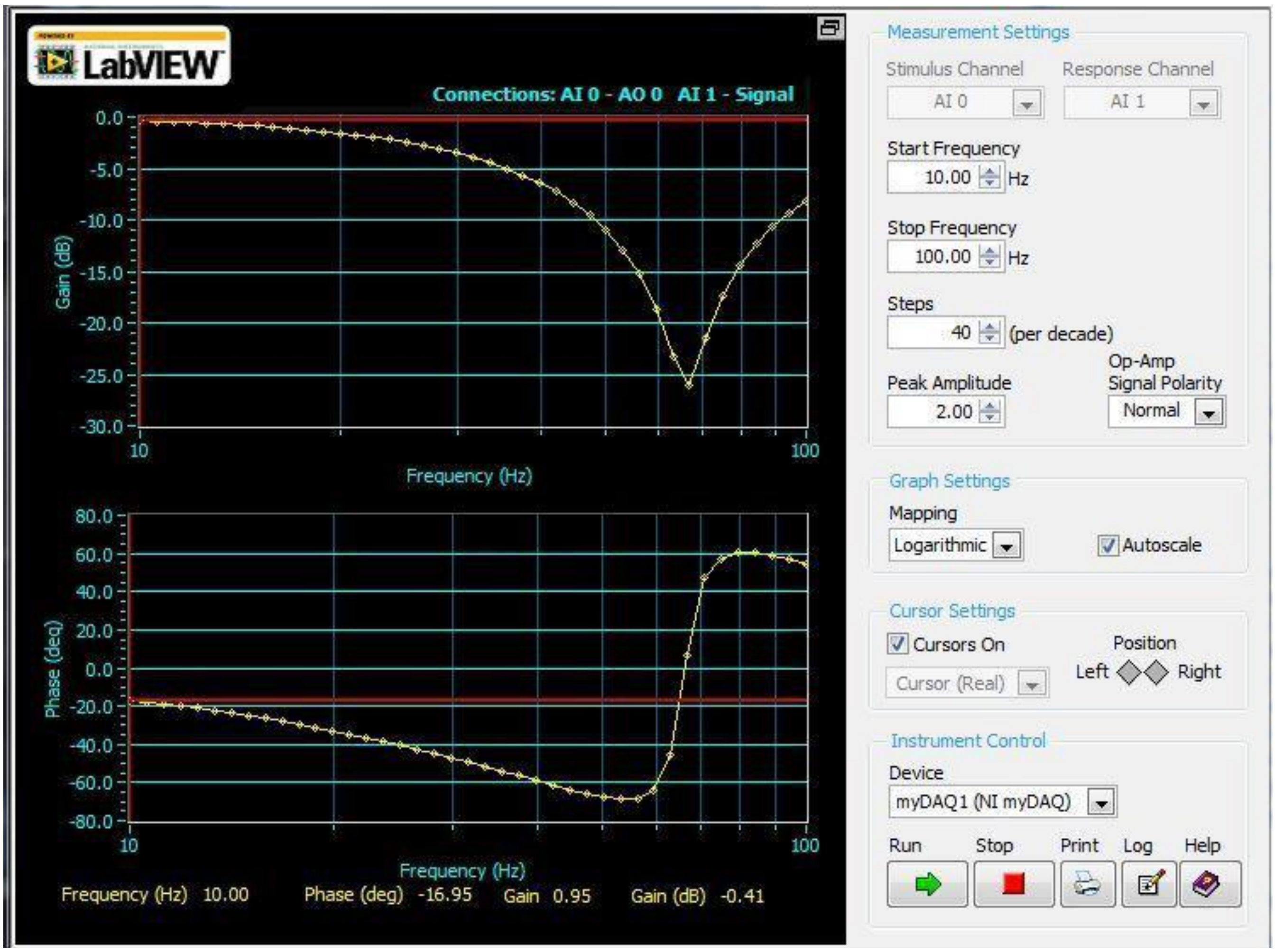

FIGURE 4.1

It can be seen clearly that frequency 50 Hz is reduced in considerable amount by this filter but yet enough 50Hz waves are present that they can’t be ignored.

As similar above, output at various stages is shown below and compares to theoretical values calculated above; it is easy to see that circuit is performing as required.

At stage 3, 7Hz High Pass Filter

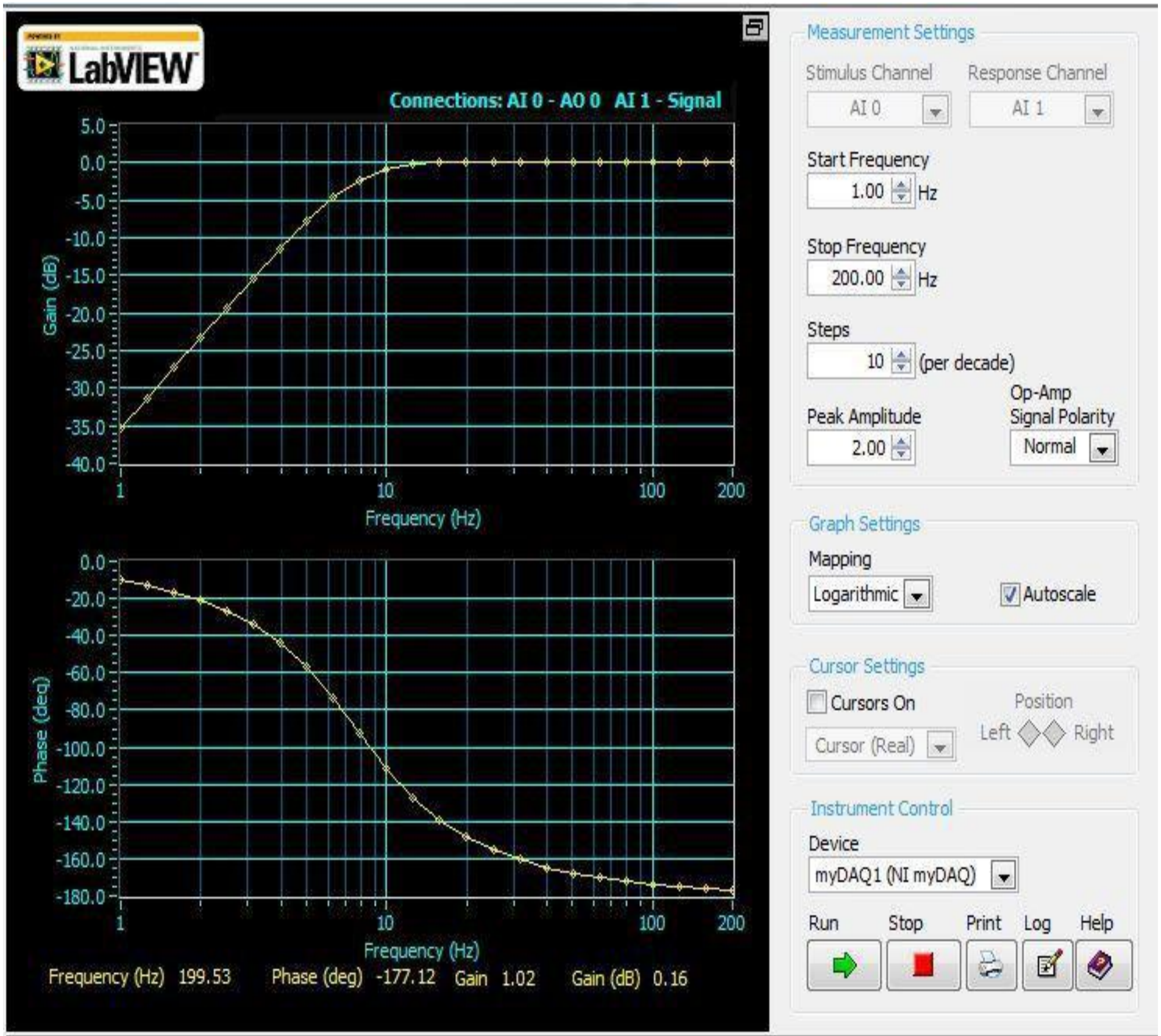

FIGURE 4.2

It can be seen clearly that frequencies below 7.2 Hz is reduced in considerable amount by this filter. Along with filtering GSR, this also filters out delta and theta waves by considerable amount.

At stage 4, 31Hz Low Pass Filter

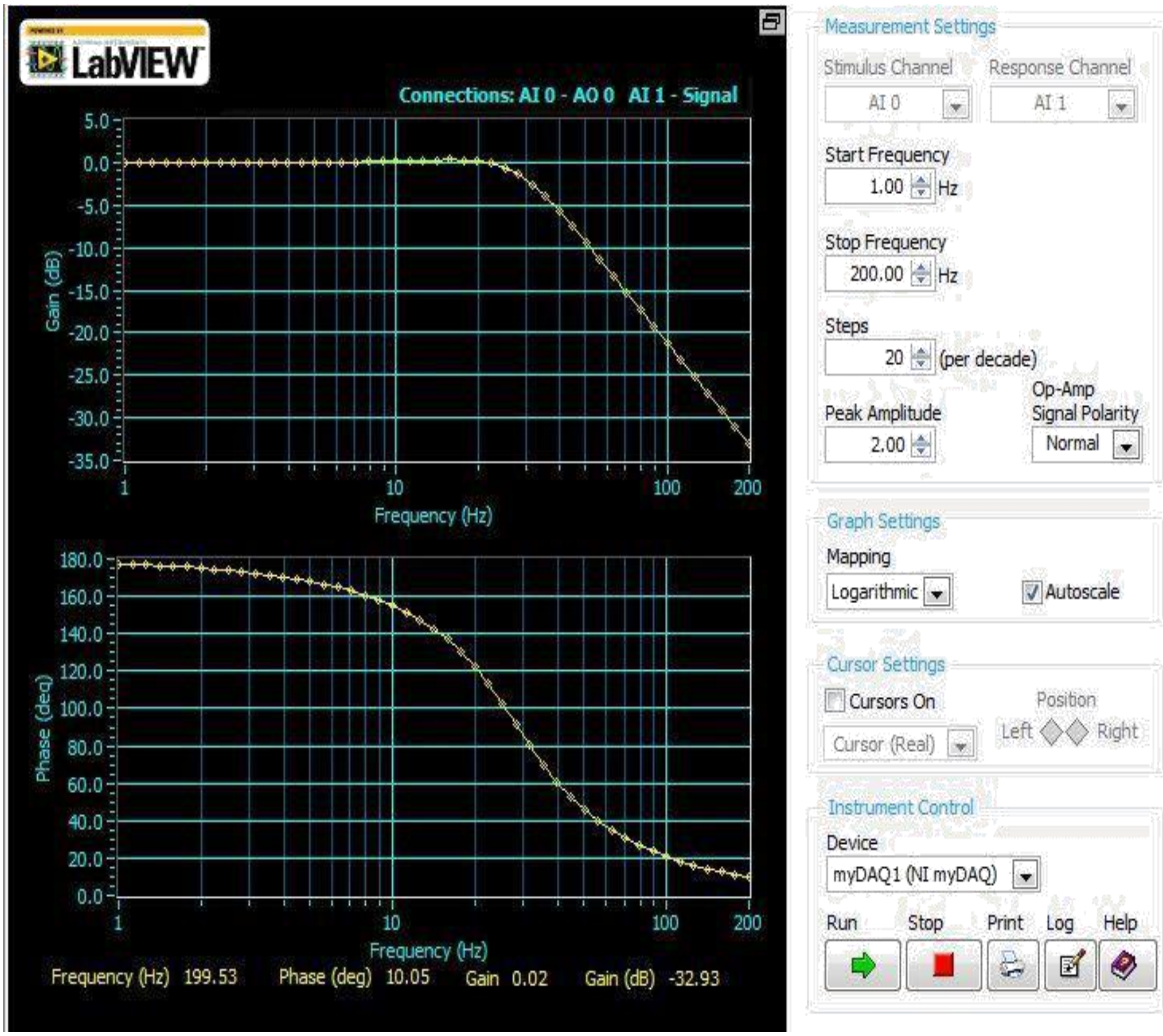

FIGURE 4.3

As clear from the first graph, the frequencies above 31 Hz have been removed considerable. Their concentration is decreasing as the frequencies go high and up to 300 Hz frequencies have been removed almost completely.

Comparison of electrodes

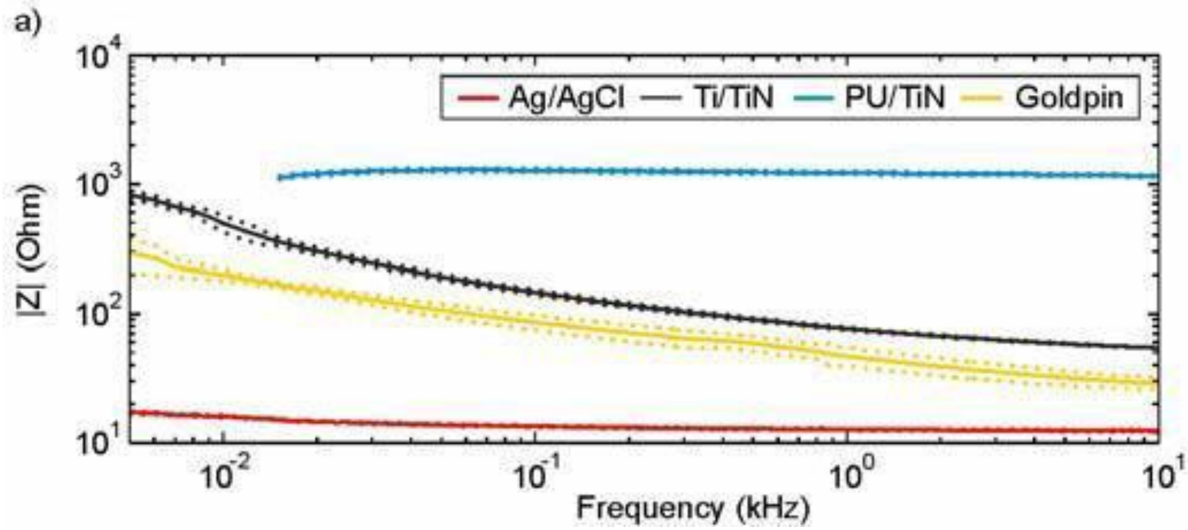

FIGURE 4.4

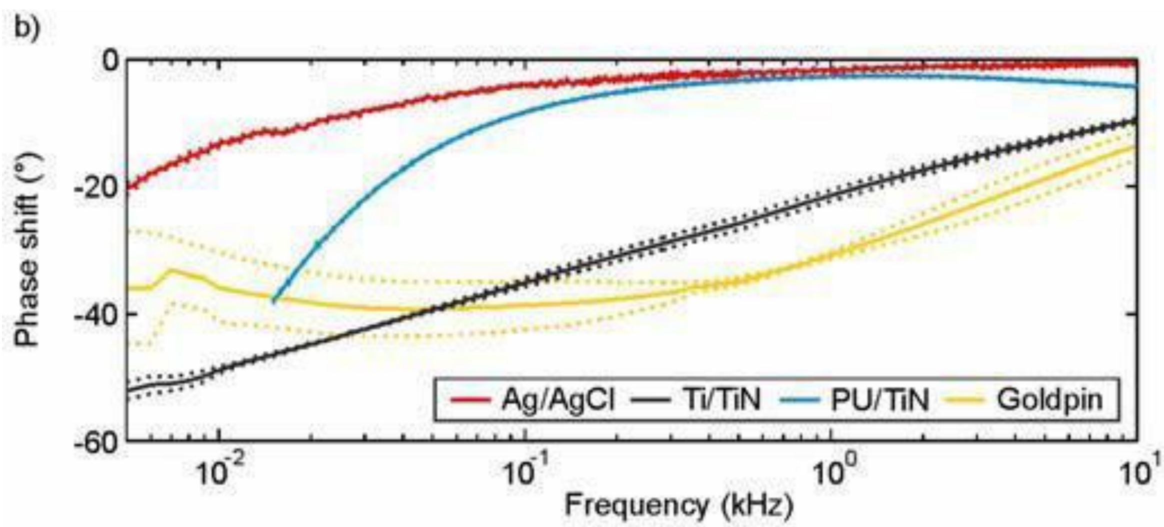

FIGURE 4.5

	EEG test	Ti/TiN	PU/TiN	Ag(Gold)	Ag/AgCl
RMSD(uv)	Resting EEG	6.9 ± 3.4	5.3 ± 0.6	6.1 ± 2.0	4.6 ± 2.1
RMSD(uv)	Alpha Activity	4.2 ± 0.8	4.4 ± 0.2	3.6 ± 0.6	3.9 ± 2
RMSD(uv)	VEP	0.6 ± 0.7	0.7 ± 0.3	1.9 ± 0.5	0.7 ± 0.4
Correlation (%)	Resting EEG	24 ± 19	59 ± 22	25 ± 13	58 ± 17
Correlation (%)	Alpha Activity	76 ± 9	73 ± 9	73 ± 9	85 ± 2
Correlation (%)	VEP	92 ± 10	95 ± 4	74 ± 22	94 ± 2

TABLE 4.1

RESULTS

Design of machine has been tested by making a software based on Fast Fourier Transform to convert input frequency domain signals into time domain for better visualization. The test subjects were of Indian origin, 18-25 age group both males and females. During testing, they had been asked to think different thoughts to verify the machine is working. Another test done to verify the design of machine was blinking eye test. Subjects were asked to blink their eyes rapidly and it changed amount of alpha and beta wave. Subjects were also asked to relax with their eyes once opened and once closed. Waves received had high amount of alpha waves.

The coding of packet was based on Neurosky mindset communications protocol:

Code of packet Received	Decoded
0x04	Attention
0x05	Meditation
0x00	Start of wave
0x0B	End of wave

The audio packet received in computer through AUX cable was of 16 bit length.

Non Zero Bytes	Wave detected	Number of packets received/sec during (128 packets/sec total)	
		Meditation (Eyes closed)	Attention (Reading novel)
8-10 (A)	Alpha	75	22
13-15 (B)	Beta	29	79
Any other (C)	None	16	18

Error in packets received 128 - (A+B +C) = 8 packets (meditation) and 9 packets (attention)

Mean error = (Total packets received – Total non-zero packets)/ Total packets received

= (256-239)/256 = 0.0664

= 6.64%

5. CHAPTER - CONCLUSIONS AND FUTURE WORK

In our project, we put forward to use real time EEG machine and from which we get signals whose frequencies are used to group attention & meditation evoked by relaxed & reading state. Allowing for each pair of channels and distinctive frequency bands, better results we get from the temporal pair of channels than the other region does, and results with higher bands of frequency that are much better than that with bands of lower frequency. These are advantages to advancement of the emotion classification framework utilizing very few EEG channels continuously. From these outcomes, we will execute real time various emotion detection system utilizing just 2 pair of channels . Later on, it can be utilized with different physiological signals, for example, GSR, and ECG, collaborated with the EEG machine to upgrade the execution of recognition of emotion with respect to the accuracy and total number of emotions.

REFERENCES

[1] R. Picard, E. Vyzas and J. Healey, "Toward machine emotional intelligence: analysis of affective physiological state", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23, no. 10, pp. 1175-1191, 2001.

[2] M. A. Khalilzadeh, S. M. Homam, S. A. Hosseini and V. Niazmand, "Qualitative and Quantitative Evaluation of Brain Activity in Emotional Stress", Iranian Journal of Neurology, vol.8 (28), pp. 605-618, 2010

[3] K. Schaaff and T. Schultz, "Towards an EEG-Based Emotion Recognizer for Humanoid Robots", in The 18th IEEE International Symposium on Robot and Human Interactive Communication, Toyama, Japan. 2009: pp. 792-796.

[4] D. P. Subha, P.K. Joseph, R. Acharya and C.M. Lim, "EEG Signal Analysis: A Survey", Journal of Medical Systems, vol. 34(2), pp. 195- 212, 2010.

[5] S.A. Hosseini, "Classification of Brain Activity in Emotional States Using HOS Analysis", International Journal of Image, Graphics and Signal Processing, vol. 4(1), pp. 21-27, 2012.

[6] K. Takahashi and A. Tsukaguchi, "Remarks on Emotion Recognition from Multi-Modal Biopotential Signals", Proceeding of the IEEE International Workshop on Robot and Human Interactive Communication, Sept. 20-22, 2004, IEEE Xplore, Japan, pp: 95-100

[7] C. T. Yuen, W. S. San, J. H. Ho and M. Rizon, "Effectiveness of Statistical Features for Human Emotions Classification using EEG Biosensors," Research Journal of Applied Sciences, Engineering and Technology, vol. 5(21), pp. 5083-5089, 2013.

[8] M. Murugappan, R. Nagarajan and S. Yaacob, "Comparison of different wavelet features from EEG signals for classifying human emotions", Proceeding of IEEE Symposium on Industrial Electronics and Applications, 2009, pp: 836-841, Kuala Lumpur.

[9] E. D. Ubeyli, "Combined Neural Network Model Employing Wavelet Coefficients for EEG Signal Classification", Digit. Signal. Process, vol. 19, pp.297-308, 2009.

[10] K. Schaaff and T. Schultz, "Towards Emotion Recognition from Electroencephalographic Signals", Proc. of 3rd International Conference on Affective Computing and Intelligent Interaction (ACII) and Workshops, pp. 1-6, 2009.

[11] Y. P. Lin, C. H. Wang, T. L. Wu, S. K. Jeng and J. H. Chen, "EEGBased Emotion Recognition in Music Listening: A Comparison of Schemes for Multiclass Support Vector

Machine", Proceeding of ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing, 2009, pp.489- 492, Taipei.

[12] Mikhail M, Ayat K.E, "Using Minimal Number of Electrodes for Emotion Detection Using Brain Signals Produced from a New Elicitation Technique", Int. J. Autonomous and Adaptive Communications Systems, vol. 6(1), pp. 80-97, 2013.

[13] K.E. Ko, H. C. Yang and K. B. Sim, "Emotion Recognition Using EEG Signals with Relative Power Values and Bayesian Network", International Journal of Control, Automation & Systems, vol. 7(5), pp.865-870, 2009.

[14] N. Jatupaiboon, S. Panngum, and P. Israsena, "Real-Time EEG-Based Happiness Detection System", Hindawi Publishing Corporation: The Scientific World Journal Volume, Article ID 618649, 12 pages, 2013,

[15] Luneski, Andrej; Konstantinidis, Evdokimos; Bamidis, Panagiotis,Affective Medicine: a review of Affective Computing efforts in Medical Informatics,Methods of Information in Medicine, vol.49, no. 3, available: eprints.whiterose.ac.uk, pp 207-218, 2010

[16] Gunes, Hatice; Pantic, Maja,Automatic, Dimensional and Continuous Emotion Recognition,Int. J. Synth. Emot., vol.1, no. 1, available: ACM Digital Library, doi: 10.4018/jse.2010101605, pp 68–99, 2010.

[17] A proposed mechanism of emotion. 1937 [classical article],The Journal of Neuropsychiatry and Clinical Neurosciences, vol.7, no. 1, available:neuro.psychiatryonline.org (Atypon), doi: 10.1176/jnp.7.1.103, pp 103-112, 1995.

[18] Maclean, Paul D.,Some psychiatric implications of physiological studies on frontotemporal portion of limbic system (visceral brain),Electroencephalography & Clinical Neurophysiology, vol.4, available: APA PsycNET, doi: 10.1016/0013-4694(52)90073-4, pp 407-418, 1952

[19] Helliwell J, layard R, Sachs J. World Happiness Report. http://www.earth.columbia.edu/sitefiles/file/Sachs%20Writing/2012/World%20Happiness%20Report.pdf.

[20] Lyubomirsky, Sonja; King, Laura; Diener, Ed,The benefits of frequent positive affect: does happiness lead to success?,Psychological Bulletin, vol.131, no. 6, available: PubMed, doi: 10.1037/0033-2909.131.6.803, pp 803-855, 2005

[21] Lin, Y. P.; Wang, C. H.; Wu, T. L.; Jeng, S. K.; Chen, J. H.,Support vector machine for EEG signal classification during listening to emotional music,2008 IEEE 10th Workshop on Multimedia Signal Processing, doi10.1109/MMSP.2008.4665061, 2008, pp.127-130.

[22] Wang, Xiao-Wei; Nie, Dan; Lu, Bao-Liang,EEG-Based Emotion Recognition Using Frequency Domain Features and Support Vector Machines,Neural Information Processing, doi10.1007/978-3-642-24955-6_87, pp.734-743, 2011

[23] Park, Kwang Shin; Choi, Hyun; Lee, Kuem Ju; Lee, Jae Yun; An, Kwang Ok; Kim, Eun Ju,Emotion recognition based on the asymmetric left and right activation,International Journal of Medicine and Medical Sciences, vol.3, no. 6, available: www.academicjournals.org, doi: , pp 201-209, 2011

[24] Frantzidis, C. A.; Bratsas, C.; Papadelis, C. L.; Konstantinidis, E.; Pappas, C.; Bamidis, P. D.,Toward Emotion Aware Computing: An Integrated Approach Using Multichannel Neurophysiological Recordings and Affective Visual Stimuli,IEEE Transactions on Information Technology in Biomedicine, vol.14, no. 3, available: IEEE Xplore, doi: 10.1109/TITB.2010.2041553, pp 589-597, 2010.

[25] Babiloni, F.; Bianchi, L.; Semeraro, F.; Millan, J. del R.; Mourino, J.; Cattini, A.; Salinari, S.; Marciani, M. G.; Cincotti, F.,Mahalanobis distance-based classifiers are able to recognize EEG patterns by using few EEG electrodes,2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol.1, doi10.1109/IEMBS.2001.1019019, 2001, pp.651-654

[26] Anh, V. H.; Van, M. N.; Ha, B. B.; Quyet, T. H.,A real-time model based Support Vector Machine for emotion recognition through EEG,2012 International Conference on Control, Automation and Information Sciences (ICCAIS), doi10.1109/ICCAIS.2012.6466585, pp.191-196, 2012.

[27] Koelstra, S.; Muhl, C.; Soleymani, M.; Lee, J. S.; Yazdani, A.; Ebrahimi, T.; Pun, T.; Nijholt, A.; Patras, I.,DEAP: A Database for Emotion Analysis ;Using Physiological Signals,IEEE Transactions on Affective Computing, vol.3, no. 1, available: IEEE Xplore, doi: 10.1109/T-AFFC.2011.15, pp 18-31, 2012.

[28] G.Chanel, J. Kon, D. Grandjean, and T.Pun “Emotion assessment: Arousal evaluation using EEG's and peripheral physiological signals”. Technical Report, Computer Vision Group, Computing Science Center, University of Geneva.

[29] Abdul-Bary Rouf Suleiman, Toka Abdul-Hameed Fatehi, “ Feature extraction techniques of EEG signal for BCI applications”, Faculty of Computer and Information Engineering Department College of Electronics Engineering, University of Mosul, Iraq, 2007.

[30] M. M. Bradley & P.J. Lang, “The International Affective Picture System (IAPS) in the Study of Emotion and Attention”, Handbook of Emotion Elicitation and Assessment, Oxford University Press, pp29-46, 2007.

[31] A., K. Ciftci, Gu Chanel, J.C Mota, L.H Viet, B.Sankur , L.Akarun , A. Caplier, and M.Rombaut "Emotion detection in the loop from brain signals and facial images". IEE Computer society, vol.2 issue1 pp. 18-31, Doi(http://doi.ieeecomputersociety.org/10.1109/T AFFC.2011.15).

[32] Mandeep Singh, Mooninder Singh and Nikhil Singhal, "Emotion Quantification along Valence Axis Using EEG Signals", International Journal of Information Technology & Knowledge Management, vol.7, no.1.

[33] Mandeep Singh, Mooninder Singh and Surabhi Gangwar, "Feature Extraction from EEG for Emotion Classification", International Journal of Information Technology & Knowledge Management, vol.7, no.1 pp.11-15 .

[34] Mandeep Singh, Mooninder Singh and Surabhi Gangwar, "Arousal Detection Using EEG Signals", International Journal of Information Technology & Knowledge Management, vol.7, no.1 pp.11-15.

[35] Mandeep Singh, Mooninder Singh, Nikhil Singhal, "Emotion Recognition along valence Axis Using naïve bayes Classifier", International Journal of Information Technology & Knowledge Management, vol.7, no. 1, pp.51-55.

[36] Mandeep Singh, Mooninder Singh and Nikhil Singhal, "ANN Based Emotion Recognition Along Valence Axis Using EEG", International Journal of Information Technology & Knowledge Management, vol.7 no.1.

[37] K. Ishino and M. Hagiwara, "A Feeling Estimation System Using a Simple Electroencephalograph", Proc. ICSMC, vol.5, pp. 4204-4209, 2003.

[38] Y. P. Lin, C. H. Wang, T. L. Wu, S. K. Jeng, and J. H. Chen, "EEG-based emotion recognition in music listening: A comparison of schemes for multiclass support vector machine", Proc. ICASSP, pp. 489-492, 2009.

[39] Y. Liu, O. Sourina, M. K. Nguyen, "Real-Time EEG-Based Human Emotion Recognition and Visualization", Cyberworlds (CW), 2010 International Conference on Proc. CW, pp. 262-269, 2010.

[40] K.Takahashi, "Remarks on emotion recognition from bio-potential signals", 2nd International Conference on Autonomous Robots and Agents, pp. 186–191, 2004.

Takahashi, Kazuhiko,Remarks on emotion recognition from bio-potential signals,in 2nd Int. Conf. on Autonomous Robots and Agents, 2005

[41] Arnaud Delorme, “EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis”, Journal of Neuroscience Methods 134, 2004.

[42] Yuan-Pin Lin, Chi-Hong Wang, Tzyy-Ping Jung,”EEG-Based Emotion Recognition in Music Listening”,IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 57, NO. 7, pp 1798–1806.

[43] Lin, Y.P., Wang, C.H., Wu, T.L., Jeng, S.K., Chen, J.H.: EEG-based emotion recognition in music listening: A comparison of schemes for multiclass support vector machine. In: ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings. pp. 489–492. Taipei (2009)

[44] Bos., D.O.: EEG-based emotion recognition [online] (2006), http://hmi.ewi. utwente.nl/verslagen/capita-selecta/CS-Oude_Bos-Danny.pdf

[45] Sourina, O., Liu, Y.: A fractal-based algorithm of emotion recognition from EEG using arousal-valence model. In: Biosignals 2011. Rome, Italy, pp.209–214, accepted (2011)

[46] Khalili, Z., Moradi, M.H.: Emotion recognition system using brain and peripheral signals: Using correlation dimension to improve the results of eeg. In: Proceedings of the International Joint Conference on Neural Networks. pp. 1571–1575 (2009)

[47] Liu, Yisi; Sourina, Olga; Nguyen, Minh Khoa, Real-Time EEG-Based Emotion Recognition and Its Applications, Transactions on Computational Science XII,Springer Berlin Heidelberg, , Available: link.springer.com, pp256-277, 2011

[48] Petrantonakis, P.C., Hadjileontiadis, L.J.: Emotion recognition from EEG using higher order crossings. IEEE Transactions on Information Technology in Biomedicine vol.14, no. 2, pp 186–197, 2010

[49] Takahashi, K.; Tsukaguchi, A.,Remarks on emotion recognition from multi-modal bio-potential signals,IEEE International Conference on Systems, Man and Cybernetics, 2003, vol.2, doi10.1109/ICSMC.2003.1244650, pp.1654-1659, 2003

[50] “5 Types Of Brain Waves Frequencies: Gamma, Beta, Alpha, Theta, Delta”, Mental Fealth Daily, 2017 [Online]. Available: http://mentalhealthdaily.com/2014/04/15/5-types-of-brain-waves-frequencies-gamma-beta-alpha-theta-delta/.”

[51] “DIY EEG (and EEG) Circuit”, Instructables.com,2017. [Online]. Available: http://www.instructables.com/id/DIY-EEG-and-ECG-Circuit/.

[52] Cooper, R., Everdell, N., Enfield, L., Gibson, A., Worley, A. and Hebden, J. (2009). Design and evaluation of a probe for simultaneous EEG and near-infrared imaging of cortical activation. Physics in Medicine and Biology, 54(7), pp.2093-2102.

[53] Jiang, L., Guan, C., Zhang, H., Wang, C. and Jiang, B. (2011). Brain computer interface based 3D game for attention training and rehabilitation. 2011 6th IEEE Conference on Industrial Electronics and Applications.

[54] Ncbi.nlm.nih.gov. (2017). National Center for Biotechnology Information. [online] Available at: http://www.ncbi.nlm.nih.gov .

Plagiarism Certificate

Submission Info

SUBMISSION ID	806343077
SUBMISSION DATE	28-Apr-2017 12:26
SUBMISSION COUNT	1
FILE NAME	Project_Report_Shubha...
FILE SIZE	1.49M
CHARACTER COUNT	71103
WORD COUNT	13016
PAGE COUNT	65
ORIGINALITY	
OVERALL	24%
INTERNET	23%
PUBLICATIONS	2%
STUDENT PAPERS	15%
GRADEMARK	
LAST GRADED	N/A
COMMENTS	0
QUICKMARKS	

Communicated Paper

IMPROVED DESIGN OF FRAMEWORK FOR SINGLE CHANNEL EEG MACHINE FOR PREDICTING STATE OF MIND OF A PERSON

Shubham Singla[1], Dilpreet Singh[2], Pradeep Kumar Singh[3], Shubhi Garg [4],
Department of CSE & IT [1] [3] [4], Department of Electronics and Communication [2]
Jaypee University of Information Technology
Waknaghat, Solan, (H.P.), India
s.singla1996@gmail.com, dilpreetsingh076@gmail.com, pradeep_84cs@yahoo.com, shubhigarg1095@gmail.com

***Abstract*— Brain emits different types of waves during different types of human activities. By measuring & classifying them properly we can predict state of mind of a person. This paper is an attempt to improve the techniques to detect brainwaves more accurately for better prediction of emotions of a person. It also discusses the issues and challenges that was faced while designing the EEG machine. An attempt to develop a cheap affordable machine that can measure the multiple type of waves of a person while he is doing various types of work is made. Software is then required that will classify waves for specific person and then predicts results and continuously improves itself with the data. It is used to predict attention or meditation state of a person in this paper.**

Keywords— Brainwaves; Electroencephalography (EEG); Brain Computer Interface (BCI)

I. INTRODUCTION

Brainwaves are one of the emerging topics in today's world and it is thought to be the key to automate and control everything just by sitting at a place [1]. Automated analysis of EEG signals has become more extensive in the recent times to include areas like lie detection and stress measurement in BCI [2]. These (brainwaves) are produced by synchronized electrical pulses from masses of neurons communicating with each other. These are categorized based on frequency of waves into following categories; Delta waves (0 - 4 Hz), Theta waves (4 - 8 Hz), Alpha waves (8 - 15 Hz), Beta waves (15–30 Hz), Gamma waves (30 Hz and above) [3]. Each set of frequencies of wave is associated with different type of activities of a person [28].

Delta waves are associated with deep sleep and unconsciousness [7]. Theta waves are associated with light sleep or self-hypnosis state of a person [7] [4]. Alpha waves are the first type of waves brain emits after waking up from comfortable sleep. During mediation, alpha waves are observed to be strongest [7]. Beta waves are the waves that are emitted during our day to day activities. Low beta waves can cause diseases like insomnia & depression [7] [3].

These waves are measured by a special instrument called EEG, a device which measures the waves by placing sensors at appropriate places on scalp [5]. It can consist no of channels i.e. number of sensors placed on scalp. Generally, more the number of sensors, more the data is collected to analyze. An EEG machine is described in this paper for the same. The output i.e. brainwave patterns has been used for analysis of state of attention/meditation of a person in further research. Affective computing has been explored in human neural responses. Some previously published works to classify different emotions, utilizes statistical features. This paper is divided into 4 sections. First section described the background of the topic. Second section literature review discusses the background of the problem. Following it, EEG machine design discusses the implementation of cheap EEG machine and placements of electrodes to record the desired signals properly in this paper.

II. LITERATURE REVIEW

In this section, previous work of different authors is discussed to analyze different ways of identifying EEG signals to improve the accuracy of the system and to recognize emotions efficiently.

Research in neuroimaging has successfully identified EEG signals correlated with attention [8], motor imagery [9], memory encoding [10], perception/recognition [11], perceived error and/or conflict [12] and which, therefore, be useful for such adaptation.

In [13], author discussed a technique based on chopper-stabilized low-noise amplifier (CS-LNA). Author used instrumentation amplifier to amplify signals by a factor of up to 4000 while taking into consideration the electrode offset voltage and noise being amplified through it. It used 2-pole Low Pass Filter (LPF) and single-differential converter with a gain of 12 db. But after considering all the factors in the paper [13] this circuit suffered from low Common Mode Rejection Ratio (CMRR) which can result in capacitors being used from common mode signals to differential mode noise. This have been the basis of our stage 1 of EEG machine discussed further in this paper. In their paper, author has also used cost efficient Ag/AgCl electrodes on scalp which can result in high charge accumulation on the metal -gel interface. This is the reason of using gold cup electrodes in our research. Support Vector Machine (SVM) classifier has been used to classify between seizure and non-seizure EEG machine learning. Seizure and non-seizure labels had been provided for training initially to the classifier. These were used to establish an optimal decision boundary between the two cases by the author. It has been recommended to use SVM classification locally with the use of specialized hardware.

Recently conducted studies used k - nearest neighbor (kNN) [30] algorithm, multilayer perceptron and SVM [15] as classifier for feature extraction [30]. Some also used DWT, lifting based wavelet transforms, optimization techniques including normalization approach [17] and different sizes of sliding windows to extract emotion related features for automated emotion recognition.

In [18], author discussed techniques to detect and correct errors in detection of signals. This can be used to improve accuracy of the system without specialized hardware for eye blink removal with techniques like Principal Component Analysis (PCA) and linear regression algorithms. Independent Component Analysis (ICA) as research found out can also be used, but it is not proven effective if applied through online techniques. As observed, only few eye blinks are required for proper estimation of covariance matrix. But the biggest challenge i.e. to detect in single trial is curbed by variable in hidden Markov tree (HMT). It is impertinent to detect appropriate noise levels to successfully implement single-trial detection of error related negativity (ERN). Super Gaussian mixtures and two state zero mean Gaussian mixture model to model small coefficients in large number i.e. large number of value with small variability is used and proven to be effective for analysis and removal of errors. Detected errors can be corrected easily by subtracting the error from the original keeping in mind the minimum threshold set before hand to detect and correct errors.

After reviewing some of the previous work, we have tried to solve two problems which may be used to improve the accuracy of the system (a) Instead of using Ag/AgCl electrodes on scalp we have used gold cup electrodes as it gives better conductivity. Hence, it leads to better detection of brain waves. (b) Hardware based solution to improve accuracy by removing errors and noise has been proposed in this paper as single error detection technique for detecting errors is not an effective way as discussed in [18].

III. IMPLEMENTATION OF DESIGN OF EEG MACHINE FOR ANALYZING BRAIN WAVES

This section describes a new cheap and affordable way of manufacturing EEG machine for personal use. EEG machine, in this paper is built on the concept of modular design and development, a design approach that subdivides a system into smaller parts called modules that can be created and used independently to ease developing debugging of machine. It has been used to measure alpha and beta waves only. It was built in 6 stages explained below:

A. Amplification of input waves

As brain waves are of few microvolts, they needed subtle amplification to remove noise and detect waves accurately. An instrumentation amplifier gives output as the multiplication of some gain G with the difference of 2 input voltages it takes. It is outfitted with input buffer amplifiers, a type of differential amplifier in fact, which doesn't require input impedance matching and thus make the instrumentation amplifier AD620AN particularly suitable for use and test as a good measuring equipment in our research. Own instrumentation amplifier can be made by using 3 op-amps, but precision resistors are needed to avoid from low CMRR [20]. To get output near to real amplifier, a higher CMRR is better.

$$G = 1 + 49{,}400 / R \text{ (in ohm) [32]} \tag{1}$$

$$G = 1 + 49{,}400 / 560 \text{ (ohm) (as used in circuit)} \tag{2}$$

$$G = 89.2 \text{ (approx.)} \tag{3}$$

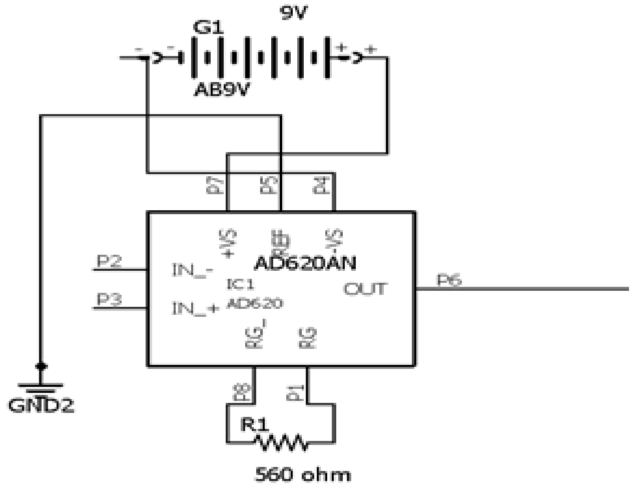

Fig 1: Amplifier with Gain (G) = 1000

B. Filtration of high frequency waves

50 Hz, frequency had maximum noise in the system. Due to this, filter is centered at 50 Hz. Two notch filters were used for the same. These filters reduced the gain around one frequency. One is used now, to cut out as much interference as possible [17] before applying any more gain to the circuit, and one is used at the end, to filter out interference that the circuit picked up during the measurement.

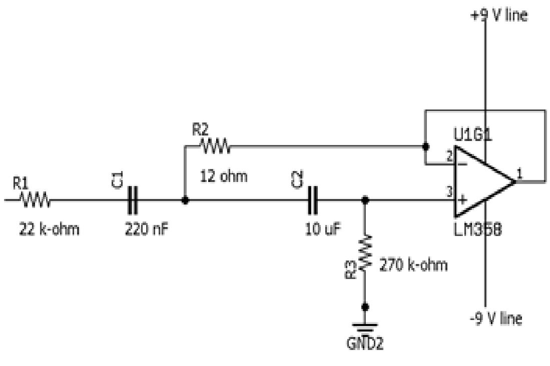

Fig 2: Notch filters for filtering frequencies above 50 Hz

C. Galvanic Skin Response (GSR) filteration

Data is measured across the skin; final readings also contained voltage/resistance from GSR across head. Due to interference, mainly by low frequency, it obscured the wanted brain data. They were easily filtered out with a high pass filter (HPF). The trade-off was it also filtered out a lot of delta wave data (the brain waves that are about 8 Hz and less).This filter with cutoff frequency of 7.23 Hz, a 2-pole HPF had been used.

Frequencies had gain of 1 approximately above this cutoff, while gain of frequencies below this was reduced continuously. The gain fell off faster as compared to a simpler resistor/capacitor circuit as it has been designed using 2 pole HPF. This 2-pole design, while approaching to 1 Hz reduces data by a factor of about 56, against a single pole which would have only reduce by nearly 7.5.

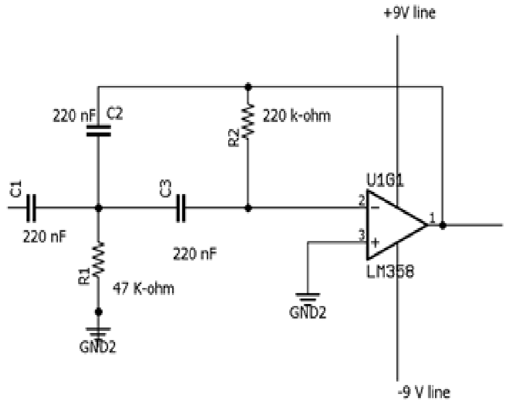

Fig 3: High Pass Filters for filtering GSR

D. *Gamma waves filteration*

RC time constant determines a cutoff frequency below which the low pass RC circuit has little attenuation but high frequencies above cutoff frequency in the signal are attenuated [22]. Real filters truncate the pulse and then impulse response is windowed to make finite impulse response to approximate the ideal.

More specifically, as the circuit has been used only to measure alpha and beta waves and max frequency stops out at 30Hz, frequencies above it were contributing a good amount of noise to data. The circuit design is like the high pass filter used previously in stage III C with a gain of 0.71 at 31.23Hz, and decreases at a rate such that it reduces by a factor of 100 as it reaches near 300Hz.

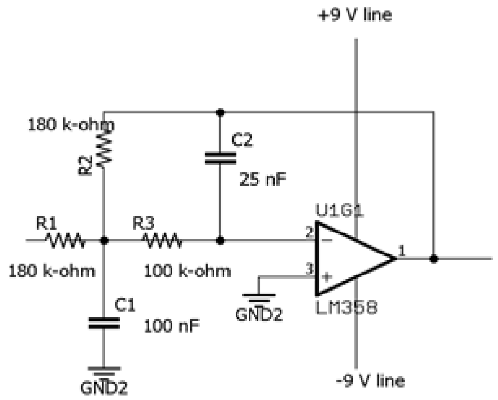

Fig 4: Circuit to retain Alpha and Beta waves

E. *Amplification for Screen visualization*

Each 6dB gain equals to doubling the voltage. Amount of ideal voltage gain depends on few factors. When coupling high powered amplifier with low voltage gain relatively, with high sensitivity input and utilizing a receiver with poorly implemented preamplifier outputs can be a problem. To power amplifier to full unclipped power this amount of voltage is needed from the preamp. A 1 Hz cutoff frequency HPF has been setup in the beginning of this circuit. On the other end, the capacitor and resistor connected in parallel can provide some additional filtering of high frequencies on a LPF.

$$Fc = 1/ (2*\pi *R*C) \tag{4}$$

$$Fc = 1/ (2*\pi *10nF*100k\Omega) =160Hz \tag{5}$$

220Ω resistor and potentiometer is the main purpose of this. A non-inverting amplifier (op-amp in this) is used. The potentiometer, whose resistance linearly changes from 0 ohms when the input is connected to the first pin to 1000 ohms and the output to the second. When the potentiometer wiper is turned to the left, effective gain by this circuit is

$$G = 1 + 100k/ (220 + 0) =455 \tag{6}$$

(10nF capacitor is ignored due to small contribution to the gain). When the wiper is turned completely to the right, the gain of the circuit is

$$G = 1 + 100k/ (220 + 1k) = 83 \tag{7}$$

On top of 89.2x gain was this 83-455 from the instrumentation amplifier. Amplitude of alpha waves varies from person to person, from 10 to 30 uV. In calculation 20 uV is used as it is the mean value, now end voltages range from

$$83*89.2*20e-6 = 0.148 \text{ V} \tag{8}$$

$$\text{to } 455*89.2*20e-6 = 0.81172\text{V}. \tag{9}$$

Before taking readings, adjusting the potentiometer has been found to be necessary while asking the subject not to move. It is necessary to keep the voltages on-screen (not over 1V). It doesn't have to be maximized to highest possible value without clipping. To avoid the error from digitally reading data, we tried not to make it too small.

F. *Filtration of noise left after previous stages*

Despite of all the previous filtering stages, 50 Hz noise was still non-ignorable in the data. It was then passed through another 50 Hz notch filter analogous to the one in section III B of this paper. Still small amount of noise persisted, which was ignored through software after the data feeder feeds data into the computer.

3.5mm male-to-male AUX type cable was used to feed the data into the computer. (like headphones/ AUX). On the cable, the first 2 notches were connected to the left and right channels, and the one furthest down is ground. 22k resistor and 220nF capacitor were connected between base of the cable and the ground line of circuit (the same line connected ground electrode). Other end was connected to microphone port of computer.

In this section, a framework on which single channel EEG machine can be designed for personal use of a person is discussed. Proposed design solution has been identified to be cheaper as compared to other models available in the market.

IV. PLACEMENT OF ELECTRODES ON SKULL

The 10–20 system or International 10–20 system is an internationally recognized method for placing EEG electrodes on scalp of person [24]. It describes in depth the procedure to place the electrodes [25]. This method was developed to ensure standardized reproducibility so that a subject's studies could be compared over time and subjects could be compared to each other. This system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex [25].

Standard conventions are used. Mid line electrode is referred by 'z' (zero). Right hemisphere electrodes are referred by even numbers (2, 4, 6, 8). Left hemisphere electrodes are referred by odd numbers (1, 3, 5, 7) [23]. Convention for Frontal is F, Temporal is T, Central is C, Parietal is P, Occipital is O. No central lobe exists but used for convention purposes only. The electrodes are placed using the standard 10-20 electrode placement manual as recognized internationally using the standard measurement tape as required by the manual [25].

The electrodes are placed at T3, T4, Fpz, Fp1, Fp2, Oz, O1, O2 at different times on different persons of age group 18-25, both male and female, all of Indian origin. The result obtained was satisfactory and measured the accuracy of up to 80% when tested against readings of EMOTIV headset.

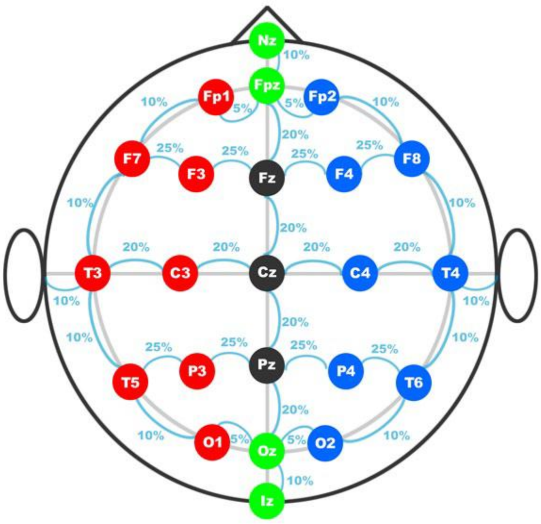

Fig 5:Postions to place electrodes [25]

V. Real Time Application

This design, if made multi-channel by either multiplexing input signals or by using various development boards can be used to identify human emotions. When persons are in high excited state like anger, this machine can help them suggest some measures like listening songs to calm down. It will require an additional software for the same. It can also be used in home automation. Instead of remote controller (which might require a person to pick-up remote and press a button), person when thinks of closing door or switching on lights, machine can automatically do it for the person by issuing relevant commands.

VI. RESULTS

Design of machine has been tested by making a software based on Fast Fourier Transform to convert input frequency domain signals into time domain for better visualization. The test subjects were of Indian origin, 18-25 age group both males and females. During testing, they had been asked to think different thoughts to verify the machine is working. Another test done to verify the design of machine was blinking eye test. Subjects were asked to blink their eyes rapidly and it changed amount of alpha and beta wave. Subjects were also asked to relax with their eyes once opened and once closed. Waves received had high amount of alpha waves.

The coding of packet was based on Neurosky mindset communications protocol [29]:

Code of packet Received	Decoded
0x04	Attention
0x05	Meditation
0x00	Start of wave
0x0B	End of wave

The audio packet received in computer through AUX cable was of 16 bit length.

Non Zero Bytes	Wave detecte d	Number of packets received/sec during (128 packets/sec total)	
		Meditation (Eyes closed)	Attention (Reading novel)
8-10 (A)	Alpha	75	22
13-15 (B)	Beta	29	79
Any other (C)	None	16	18

Error in packets received 128 - (A+B +C) = 8 packets (meditation) and 9 packets (attention)

Mean error = (Total packets received – Total non-zero packets)/ Total packets received

= (256-239)/256 = 0.0664

= 6.64%

VII. CONCLUSION AND FUTURE SCOPE

Manufacturing of a single channel cost efficient EEG machine prototype is discussed in this paper. It does not use complex algorithms like face detection to improve accuracy. Proposed model may be utilized as an alternative in place of the available models. The acceptability of proposed scheme may be considered as it is a cheaper in comparison to other options available. It can be tested by asking subject to blink eyes rapidly. Blinking eyes will change the wave pattern being observed on the screen. This design can be coupled with cost efficient high processing capable micro controllers like Raspberry pi to make it n-channel machine and use it for further research. By making adequate adjustments it can be used in real time applications as described in this paper.

REFERENCES

[1] C. Frith, and R Corcoran, “Exploring ‘theory of mind’ in people with schizophrenia,” Psychological Medicine, vol. 26, no. 3, pp.521-525, 1996.

[2] R.W. Picard, E. Vyzas and J. Healey, “Toward Machine Emotional Intelligence: Analysis of Affective Physiological State”, IEEE T. Pattern Anal., vol. 23, pp.1175-1191, 2001.

[3] D. P. Subha, P.K. Joseph, R. Acharya and C.M. Lim, "EEG Signal Analysis: A Survey", Journal of Medical Systems, vol. 34, no. 2, pp. 195-212, 2010.

[4] L. Zylowska, “ The Mindfulness Prescription for Adult ADHD”, Trumpeter, Boston and London, 2012.

[5] “Electroencephalography”, En.wikipedia.org, 2017. [Online]. Available: https://en.wikipedia.org/wiki/Electroencephalography.

[6] M. A. Khalilzadeh, S. M. Homam, S. A. Hosseini and V. Niazmand, “Qualitative and Quantitative Evaluation of Brain Activity in Emotional Stress”, Iranian Journal of Neurology, vol. 8, no. 28, pp. 605-618, 2010.

[7] "5 Types Of Brain Waves Frequencies: Gamma, Beta, Alpha, Theta, Delta", Mental Health Daily, 2017. [Online]. Available: http://mentalhealthdaily.com/2014/04/15/5-types-of-brain-waves-frequencies-gamma-beta-alpha-theta-delta/.

[8] Gevins, A., Smith, M., McEvoy, L., Leong, H., Le, J.: Electroencephalographic imaging of higher brain function, Philosophical Transactions of the Royal Society, ser. B London, U.K.,vol. no. 354, pp. 1125–1134, 1999.

[9] Babiloni F., “Linear classification of low-resolution EEG patterns produced by imagined hand movements”, IEEE Transaction Rehab. Eng., vol. 8, pp. 186–188, June, 2000.

[10] Tallon-Baudry, C., Bertrand, O., Peronnet, F., Pernier, J. : Induced gamma-band activity during the delay of a visual short-term memory task in humans, J. Neurosci., no. 11,pp. 4244–4254, 1998.

[11] Thorpe, S., Fize, D., Marlot, C., “Speed of processing in the human visual system”, Nature, pp. 520–522, 1996.

[12] Miltner, W.H.R., Braun, C.H., Coles, M.G.H., “Vent-related brain potentials following incorrect feedback in a time estimation task: Evidence for a generic neural system for error detection”, J. Cog. Neurosci., pp. 788–798, 1997.

[13] Verma, N., Shoeb, A., Bohorquez, J., “A Micro-Power EEG Acquisition SoC With Integrated Feature Extraction Processor for a Chronic Seizure Detection System” , IEEE journal of solid-state circuits, vol. 45, no. 4, April, 2010.

[14] Lung, C.H., Zaman, M., Nandi, A., “Applications of clustering techniques to software partitioning, recovery and restructuring”, October 2004.

[15] Wang, X.W., Nie, D., “EEG-Based Emotion Recognition Using Frequency Domain Features and Support Vector Machines”, ICONIP, Part I, LNCS 7062, pp. 734–743, 2011

[16] Park, K.S., Choi, H., Lee, K.J., “Emotion Recognition based on the asymmetric left and right activation”, International Journal of Medicine and Medical Science Vol. 3 no. 6, pp. 201-209, June, 2011.

[17] Maheswari, S.U, Hemanth ,J., ”Performance enhanced image steganography systems using transforms and optimization techniques”, Springer Science, Business Media New York, 2015.

[18] Parra, L.C., Spence C. D.: Response Error Correction—A Demonstration of Improved Human-Machine Performance Using Real-Time EEG Monitoring, IEEE transactions on neural systems and rehabilitation engineering, vol. 11, no. 2,June, 2003.

[19] "Operational amplifier", En.wikipedia.org, 2017. [Online]. Available: https://en.wikipedia.org/wiki/Operational_amplifier.

[20] M. A. Smither, D. R. Pugh, L. M. Woolard, "CMRR analysis of the 3-op-amp instrumentation amplifier", Electron. Lett., vol. 13, no. 20, pp. 594, 1977.

[21] Anon, (2017). [online] Available at: http://ppqq32.tistory.com/entry/LPFLow-pass-filter

[22] En.wikipedia.org. (2017). Low-pass filter. [online] Available at: https://en.wikipedia.org/wiki/Low-pass_filter [Accessed 18 Nov. 2016].

[23] En.wikipedia.org. (2017). 10-20 system. [online] Available at: https://en.wikipedia.org/wiki/10-20_system [Accessed 11 Oct. 2016].

[24] M. Khazi, A. Kumar and V. M J, "Analysis of EEG Using 10:20 Electrode System", International Journal of Innovative Research in Science, Engineering and Technology, vol. 1, no. 2, December 2012

[25] 10-20 Electrode placement manual 2017. [Online]. Available: https://www.trans-cranial.com/local/manuals/10_20_pos_man_v1_0_pdf.pdf.

[26] Herbert, H. (1958). Report of the committee on methods of clinical examination in electroencephalography. Electroencephalography and Clinical Neurophysiology, 10(2), pp.370-375

[27] Y. Cai, “Ambient Diagnostics”, CRC Press, 1 Dec 2014, p 21

[28] S.A. Hosseini, "Classification of Brain Activity in Emotional States Using HOS Analysis", International Journal of Image, Graphics and Signal Processing, vol. 4(1), pp. 21-27, 2012.

[29] “MindSet Communication Protocol”, Neurosky, Brain computer Interface technology, June, 2010. [Online]. Available at : http://wearcam.org/ece516/mindset_communications_protocol.pdf

[30] U. I. Awan, U.H. Rajput, G. Syed, R. Iqbal, I. Sabat, M. Mansoor, “ Effective Classification of EEG Signals Using K-Nearest Neighbor Algorithm” pp. 120-124, 2016.

[31] C. Rambabu, B. Rama Murthy, “ EEG Signal with Feature Extarction using SVM and ICA Classifier”, Journal of Computer application, Vol. 85 no. 3, pp. 1-7, January, 2014.

[32] “Low cost and Low Power Instrumentation Amplifier”, Analog Device, 1999, [Online]. Available at : http://users.ece.utexas.edu/~valvano/Datasheets/AD620