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INSTITUTE OF ENGINEERING

THAPATHALI CAMPUS

A Major Project Proposal

On

Human-Computer Interaction using Neuromuscular Signals

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Submitted To:

DEPARTMENT OF ELECTRONICS AND COMPUTER ENGINEERING

THAPATHALI CAMPUS

KATHMANDU, NEPAL

February, 2020

ACKNOWLEDGEMENT

We would like to use this opportunity to express our deepest gratitude to our project supervisor, Mr. Dinesh Baniya Kshatri, for all the guidelines and motivation he has provided. We would also like to expand our gratitude to our lecturers and classmates who have helped us directly and indirectly.

Finally, we are very thankful to the Department of Electronics and Computer Engineering, IOE Thapathali Campus for providing us this opportunity to conduct this project.

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ABSTRACT

This project is about designing a Human Computer Interface that reads Electromyography signals from different parts of Articulatory System. The signal is perceived from different muscles of articulatory system that is associated with internal articulation of voice commands. The signal which is in the range of microvolts is amplified to volts using instrumentation amplifiers and artifacts occurred is filtered in two steps combined with high pass and low pass filters. Amplifiers and filters are embedded in a printed circuit board along with Arduino and Bluetooth module for remote communication. Digitalized signal from Arduino is sent to a remote computer via Bluetooth. Received signal is pre-processed for feature extraction which is fed to the neural network to recognize internally articulated English alphabets or digits or words. Finally, the recognized information is displayed on the computer screen.

Keywords: Electromyography, Internal Articulation, Articulatory System

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List of Abbreviations

ADC	Analog to Digital Converter
ALS	Amyotrophic Lateral Sclerosis
AR	Auto regression
BCI	Brain Computer Interaction
CMRR	Common Mode Rejection Ratio
CN	Cranial Nerve
CTC	Connectionist Temporal Classification
DFT	Discrete Fourier Transform
DTCWT	Dual Tree Complex Wavelet Transform
ECG	Electrocardiography
ECoG	Electrocorticography
EEG	Electroencephalography
EMG	Electromyography
EMS	Electrical Muscle Stimulation
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
GBP	Gain-Bandwidth Product
HPF	High Pass Filter
IDE	Integrated Development Environment
IIR	Infinite Impulse Response
LPF	Low Pass Filter
LSB	Lower Significant Bit
MUPA	Motor Unit Action Potentials
NEMS	Neuromuscular electrical stimulation
PNS	Peripheral Nervous System
PWM	Pulse Width Modulation
RCA	Radio Corporation of America
RNN	Recurrent Neural Networks
SNR	Signal to Noise Ratio
STFT	Short-Time Fourier Transform
UART	Universal Asynchronous Receiver/Transmitter
WER	Word Error Rate

1. INTRODUCTION

1.1 Background

Electrophysiology is the science and technique of studying the electrical phenomena that play a role in the life of plants and animals. These phenomena include the membrane potential, being ubiquitous among living cells, and its changes, which constitute signals playing an important part in the physiology of any organism. These signals may be slow changes caused by the changing concentration of some chemical substance, or the fast-transient peaks called “action potentials” or “spikes”, which arise by the fast opening of molecular “gates” in the membrane of neurons and similar types of electrically active cells.

Movement of body parts of living being is fully coordinated and controlled by their brains. Both voluntary and involuntary movements are controlled by brain. When brain wants to move a muscle of a body part, it informs ‘motor cortex’. Motor cortex calculates the amount of contraction and relaxation needed for a muscle to move and it sends the signal to spinal cord. The spinal cord then sends the signal to axiom, which is connected to a particular muscle and muscle is moved in the coordinated direction. All these signals from the brain to the muscles are in the form of electric signals. The feeble electric signals cannot be felt by the humans themselves but it can be detected after proper amplification. There exists devices such as an electroencephalograph (EEG) to do so. Besides EEG there exists many techniques for studying internal speech articulation. They can be listed as follows:

- Electromyography (EMG)
- Electrocorticography (ECoG)
- Permanent Magnet Sensors
- Ultrasound
- Optical Camera
- Vocal Tract Resonant Signals

During production of speech from vocal cord complex series of finite and coordinated neuromuscular communication is associated. For the complete generation of sound more than 100 muscles are involved. When a person articulates a word internally without acoustic vocalization and no significant movements in facial muscle and tongue, more than 15 muscles which are parts of speech system, are neurologically activated. These particular muscles receive feeble electrical signals from the PNS. The electrical impulse perceived in the form of potential difference can be used to decode the actual word that the person is articulating. [1]

Using human computer interaction through neurological signals is a relatively new way of human-machine interaction. In practice, inputs are being given through significant movement of body parts whether the system is manually controlled, touch control or gesture control. In this project, inputs for machines are generated from neuromuscular signals that arises as action potential on muscles as voluntary muscular operation during internal articulation of speech.

1.2 Motivation

There were some amazing researches and projects which are similar to our project. Our idea of this project is motivated mostly by ‘Backyard Brains’ and ‘AlterEgo’ which are described as follows:

Backyard Brain is a team of engineers, scientists and researchers that have been constantly researching on inner working of nervous system. And have designed some interface and hardware with cheap electronics that can help students in providing insight into the working of the nervous system. The equipment for conducting such experiments costs much but they aim to provide students below graduation to do experiments on nervous system maintaining ethics regarding experimentation on living beings. [2]

AlterEgo is a personalized wearable silent speech interface that allows its users to silently converse with a computing device without any voice or any discernible movements - thereby enabling the user to communicate with devices, AI assistants, applications or other people in a silent, concealed and seamless manner. A user's intention to speak and internal speech is characterized by neuromuscular signals in internal speech articulators that are captured by the AlterEgo system to reconstruct this speech. This interface is used to facilitate a natural language user interface, where users can silently communicate in natural language and receive aural output (e.g.: - bone conduction headphones), thereby enabling a discreet, bi-directional interface with a computing device, and providing a seamless form of intelligence augmentation. [1]

This project is selected as it has interfacing of brain signals with computer. Brain computer interface (BCI) is new field for research and product development. In this context, this project provides platforms for research on this field. It is also intended to help on one of the evolving fields of science and technology i.e. bio-technology.

1.3 Problem Definition

Since the development of the very first computer, human-computer interaction has always required to have some form of physical action as an input to the computer. These traditional input devices include keyboards, mouse, joystick, cameras, microphones etc. Although these methods possess high accuracy and convenience, they suffer from lack of privacy. And it may not be possible for everyone to use such traditional means for interacting with a computing device. The traditional system has also been proved to be very slow in today's world. Speech interaction somewhat tackles this issue but is still subjected to privacy problems. The proposed system in this project tackles all these problems and provides a secure and faster interaction between a human and a computing device. And the proposed system works the same for everyone disregarding their disabilities.

1.4 Project Objectives

The main objectives of our projects are:

- To develop a system to extract EMG signals from the articulatory muscles.
- To transmit the extracted EMG signals wirelessly to a remote computer.
- To process the wirelessly received signals and generate the corresponding text
- To display the generated text on the remote computer

1.5 Project Scope and Applications

The scope of this project includes the extraction of impulses from different muscles of our articulatory system that are activated during internal articulation of speech. Several trained neural networks are used to extract the signals. This project does not include the decoding of signals produced during articulation of sentences and special characters. It is not compatible for languages other than English. The interface is unidirectional and does not include the control of any devices.

This project is applicable in many research-oriented bio-electronic product development for medical and research purposes. As this project provides a new way of human and computer interaction, it can be used to develop a system on that basis. Following are some of the applications of this project.

1.5.1 Human Computer Interfacing System using Neuromuscular Signals

The signals generated from motor neurons during speech articulation can be used as commands for performing specific tasks like moving mouse cursers, typing a letter, clicking an icon etc. This method could be a faster approach for human computer interaction.

1.5.2 Communication Medium for ALS Patient

Using human computer interface, Amyotrophic Lateral Sclerosis (ALS) patient can give instruction to computer. Patients suffering from ALS has lost ability to move voluntary body parts due to malfunctioning of nerves cells in brain and spinal cords. The gradual paralysis of body parts makes person unable to do any voluntary controls over body parts. Those patients can utilize this project as a method of input for computer. The signals from articulatory muscles of patients can be taken as commands for various tasks like pronouncing the words, changing speed and direction of wheelchair, giving commands for other devices etc.

1.5.3 Communication in Places where Speech is not possible

This project is also applicable in some places where audio signals cannot be used for communication. In space, this project stands as a viable means of communication due to absence of propagating medium.

Similarly, for other situations like communication under water by marine troops, Sea Explorer, extremely crowded areas during emergencies and peoples in low air pressure areas like mountaineers in high mountains can also communicate using same technique.

1.5.4 Multilingual Device

Extending this project by implementing soundless hearing using bone conduction method can be developed as a multilingual device. The device can translate one language into another which facilitates the communication between people who doesn’t understand each other’s language.

1.6 Report Organization

The material presented at the report is organized into eleven chapters. Chapter 1 is an introduction section which mainly describes the background, objective, scope and application of the project. It also focuses on the need of the project. Chapter 2 presents brief summaries of all existing works that have already been carried out in the related field. It describes the activities related to a project that have been carried by some specific people. Chapter 3 illustrates the theoretical and mathematical models required in our project. Chapter 4 explains about the effect of noise and the types of noise that the system designed in our project is susceptible to. Chapter 5 provides an account of the hardware and software requirements of the project. This chapter also summarizes the implementation process of the used hardware and software. Chapter 6 explains in details a particular sequence in which the work has been carried out along with detailed procedures, block diagram or data flow diagram which illustrate the explanation of how the hardware and software are used to accomplish the project. Chapter 6 also contains the details of the implementation of the things that have been explained in the methodology. In short, it describes how the methodology is implemented. It explains how we have used the programming language or tools to implement the methodology. Chapter 7 contains the result of the project. In other words, it shows the total progress done on the project till date. The output is shown in graphical form as well. Chapter 8 signifies the problems faced during the course of design of the system in the project. It also briefly states the analysis of the result. Chapter 9 gives the information about the tasks in the project that are still remaining. Chapter 10 contains the additional topics like cost estimate, project schedule and Chapter 11 includes the references used for our project and this report.

2. LITERATURE REVIEW

There has been a number of attempts in electrophysiology for analysis of neural activities. "AlterEgo: A Personalized Wearable Silent Speech Interface", a research accomplished by Arnav Kapur, Shreyas Kapur and Pattie Maes which was published by MIT Media Lab in 2018, presents a natural extension of the user's own cognition by enabling a silent, discreet and seamless conversation with machines and people. It presents a wearable silent speech interface that allows users to provide arbitrary text input to a computing device or other people using natural language, without discernible muscle movements and without any voice command i.e. without explicitly saying anything. The nerve impulses were sourced as seven channels from laryngeal region, hyoid region, levator anguli oris, orbicularis oris, platysma, anterior belly of the digastric mentum using electrodes on the outer skin. [3]

According to neuroprosthetics experiment, "Control Machines with your Brain" done from 2009-2017 by Backyardbrains, a team of researchers and engineers, the EMG signals were extracted from Muscle SpikerShield which was interfaced with micro-controller and the data obtained was visualized in Spike Recorder App developed by the team. The research was further extended as Human-Machine Interfaces, which included control of robotic arm, video games and voiceless communication. [4]

A research paper by Michael Wand and Tanja Schultz named "SESSION-INDEPENDENT EMG-BASED SPEECH RECOGNITION" describes the method of speech recognition by surface EMG signals. By recording the electric active potentials of human articulatory muscles, it can be decoded into a speech that person is vocalizing. Speech recognition using EMG signals dates back to 1980s. 93% accuracy was observed on 10-word vocabulary. It suggests that good result can be obtained even for the signals taken when words are silently articulated. [5]

"Electrical Stimulated as a Modality to Improve Performance of the Neuromuscular System", a research paper by Vanderthommen Marc and Duchateaus Jacques in October 2007 transcutaneous neuromuscular electrical stimulation (NEMS) can modify the order of motor unit recruitment and has a profound influence on the metabolic demand associated with producing a given muscular force. Tetanic contractions elicited by pulses of high intensity and short duration induce a high metabolic stress in the muscle, contribute to the reversal of motor unit recruitment, and improve the maximal capability of the neuromuscular system primarily not only through increased force-generating capacity of the muscle but also through intensified voluntary activation. [6]

A research paper “End-to-end neural networks for subvocal speech recognition” written by Pol Rosello, Pamela Toman and Nipun Agarwala attempts to perform session independent subvocal speech recognition by leveraging character-level recurrent neural networks (RNNs) and the connectionist temporal classification loss (CTC). They utilized EMG-UKA trial coprus’s two hours of data to train their CTC models. Although the accuracy of their model is not mentioned, they did express some measures to improve the field to silent speech recognition through EMG signals in their paper. [7]

Munna Khan and Mosarrat Jahan wrote a paper “The Application of AR Coefficients and Burg Method in Sub-vocal EMG Pattern Recognition” which showcases successful recognition of Hindi phonemes (Ka, Kha, Ga, and Gha) with accuracy of about 75.5% to 80%. They studied burg algorithm techniques for EMG spectral analysis and used reflection coefficients and AR coefficients as features of sub-vocal EMG signal to recognize the patterns of sub-vocal phonemes. They concluded that the pattern recognition in EMG signal using reflection coefficients and AR coefficients is highly efficient and can be used to develop a real time module. [8]

In “Development of sEMG sensors and algorithms for silent speech recognition”, a research paper published by Geoffrey S. Meltzner, James T. Heaton et al., a new system capable of recognizing silently mouthed words and phrases based completely on surface EMG signals has been described. They tested a system of sensors and algorithms during a series of subvocal speech experiments involving more than 1,200 phrases generated from a 2,200-word vocabulary and obtained 91.1% recognition rate i.e. word error rate (WER) of 8.9%. They prepared their dataset performing experiments on a total of 19 subjects (11 males and 8 females) ranging from 20-42 years in age with no speech or hearing disabilities. They had applied discrete-cosine Fourier transform in order to obtain coefficients of the signal for the training set. [9]

Chuck Jorgensen and Kim Binsted in 2005 published a paper "Web Browser Control Using EMG Based Sub Vocal Speech Recognition" which describes they had trained six subvocally pronounced control words, 10 digits, 17 vowel phonemes and 23 consonant phonemes using a scaled conjugate gradient neural network. They had recorded the surface EMG signals of frequency range 30-500 Hz from the larynx and sublingual areas below the jaw, filtered them, sampled them at 2000 Hz and transformed into features using a Kingsbury's Dual Tree complex wavelet transform (DTCWT) and short time Fourier transform (STFT). They had also designed a notch filter to eliminate line noise at 60 Hz. They had obtained an average of 92% accuracy. Using the trained control words, they performed sub vocal web browsing. [10]

3. THEORETICAL AND MATHEMATICAL MODELING

3.1 Theoretical Conditions

3.1.1 Articulatory Mechanism

In articulatory system during the production of audible sound, brain controls all the functions related to contraction and expansion of different muscles to produce a particular sound. Different nerves are used as signal transmission media through different nerves to control the muscles related to the activity.

There are three different mechanisms of acoustic speech namely, speech respiration, phonation and articulation. Respiration provides pressure and vibration on muscles necessary for the production of speech. Phonation is the process of sound production by passing air through larynx (voice box) tissue. Articulation is soft movement of articulatory organs to imitate speech without production of audible sound.

Different types of nerves involved in the articulatory system and respective muscles movement are tabulated below.

Table 3-1: Nerves and Muscle movements in Articulatory System.

S.N.	Nerve	Movements	Sensory Functions
1	Trigeminal Nerve (CN V)	Biting and chewing	Sensory data from palate, teeth and anterior tongue
2	Facial Nerve (CN VII)	Facial muscle	Sensation to the external ear
3	Glossopharyngeal Nerve (CN IX)	Elevation of Pharynx and larynx	Sensation to posterior tongue and upper pharynx
4	Vagus Nerve (CN X)	Elevation of the palate phonation	Sensory data from external ear, tongue and larynx
5	Hypoglossal Nerve (CN XI)	Movement of the tongue	Sensory data from the tongue

Plasma membranes of neurons like all other cells, have an unequal distribution of ions and electrical charges between the two sides of the membrane. Normally, cell has positive charge (Na+) outside the plasma membrane and negative charge (K-) inside the membrane. The difference resulting from their potential is known as resting potential which is in the order of millivolts. Exchange of ions occurs in the plasma membrane of cell for maintaining unequal concentration of the charges which is known as sodium-potassium pump. When a neuron sends information down an axon, away from the cell body of a neuron, temporary reversal of electrical potential occurs along the membrane for few milliseconds which is defined as action potential. Action potential begins at one spot and spreads to adjacent area of the membrane, propagating message along the length of cell membrane. Sodium and potassium ions passes through protein channel gates that can be opened or closed. After the generation of action potential, there is a brief refractory period during which membrane can't be stimulated, this prevents the message from being transmitted backward.

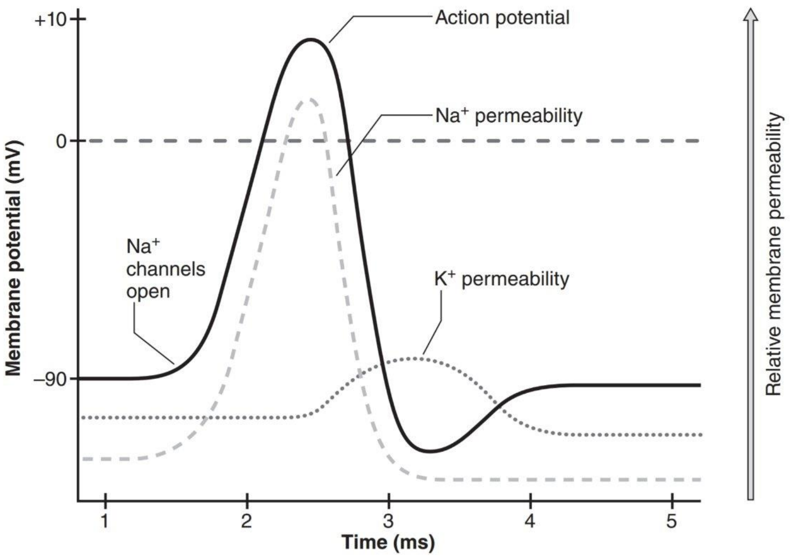

Figure 3-1: Time Course of the Muscle Fiber Action Potential [11]

Triggering muscle movement begins in the motor cortex, where series of action potentials occur, signals the spinal cord and the information related to the movements conveyed to the relevant muscles via motor neurons. This begins with upper motor neurons that carry signals to the lower motor neurons. The lower neurons are the actual instigators of muscle movement as they innervate the muscle directly at the neuromuscular junction. The innervation causes the release of calcium ions within the muscles ultimately creating a mechanical change in the tension of the muscles which involves depolarization. Thus, generated fluctuations in the electrochemical gradient resulting from muscle response during nerve stimulation of muscles are measured using Electromyography (EMG). [12]

For the analysis of superimposed motor unit action potentials (MUPAs) generated from several motor units, the EMG signals can be decomposed into their constituents MUPAs distinguished by their characteristic shapes. The shape and size depend on where the electrode is located with respect to the fibers and are different if electrode position is altered slightly. [13]

3.1.2 Articulatory Muscles

Different facial muscles are involved in the activation of the active articulators for articulation. They are divided into different regions which are listed below:

- Labial region
- Lingual region
- Mandibular region
- Palatal region
- Pharyngeal region

Selecting the right muscle for extracting the EMG signal is very essential. Many factors such as noise susceptibility, signal strength, cross-talk, signal frequency, etc. depend on the selection of the muscle. Some of the basic criteria to be followed while selecting the muscles are as follows:

- Select the muscle where it is convenient to place the electrodes.
- Distance from the electrode to the muscle should be minimum.
- Size of muscle should be large enough to avoid cross-talks.
- Configuration to be followed for signal extraction (bipolar or monopolar) also determines which muscle to select.
- Size of the electrode and the type of electrode should be considered before selecting the muscles.

Some of the major muscles fulfilling the above criteria are listed as below:

3.1.2.1 Levator Anguli Oris

Levator Anguli Oris is a facial muscle close to the mouth opening that lifts the angle of the mouth. This muscle is innervated by the buccal branch of the facial nerve (CN VII). When activated, the levator anguli oris lifts the angle of the mouth, thus participating in creating a smile. Contractions of this muscle produce a facial expression associated with self-confidence.

3.1.2.2 Zygomaticus Major

The zygomaticus major muscle is a paired facial muscle that extends between the zygomatic bone and the corner of the mouth. It is one of the two zygomatic muscles (major and minor) that lie next to each other in the cheek area. An activated zygomaticus major muscle is involved in creating an expression in the human face known as a smile. The nerve supply of the zygomaticus major is received from the zygomatic and buccal branches of the facial nerve (CN VII).

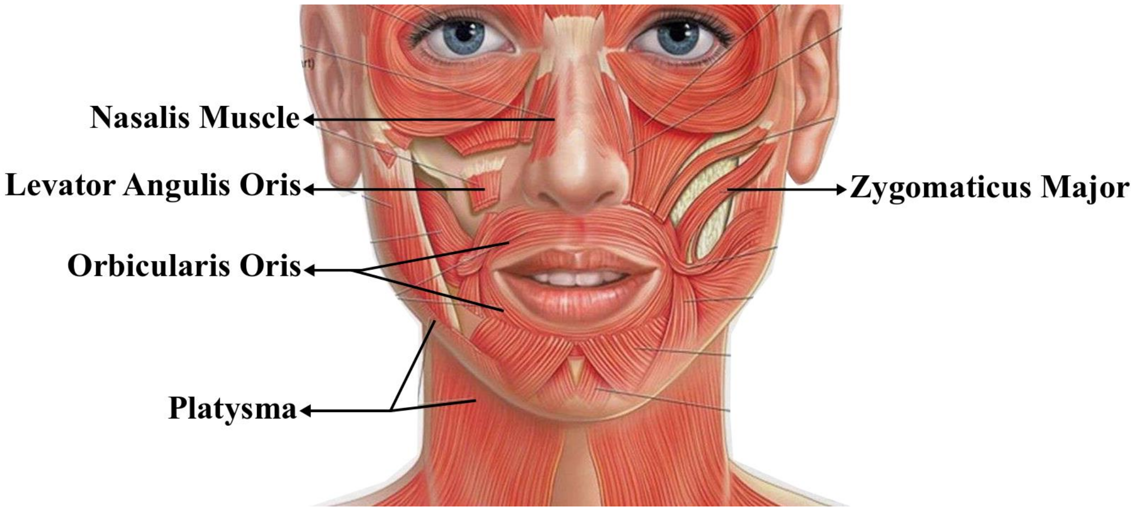

Figure 3-2: Active facial muscles

3.1.2.3 Platysma

The platysma (also platysma muscle, Latin: platysma) is a wide, flat, superficial neck muscle extending from the lower part of the face to the upper thorax. The platysma is a paired thin and superficial muscle arising from the upper parts of the shoulders and inserting into the mouth area. Contractions of the platysma depress and wrinkle skin of the lower face and the mouth. The platysma also contributes to forced depression of the mandible. The platysma is innervated by the cervical branch of the facial nerve (CN VII).

3.1.2.4 Anterior Belly of Digastric

The anterior belly of the digastric (Latin: venter anterior musculi digastrici) is one of the two bellies of the digastric muscle. The anterior belly is smaller than the posterior belly, and it develops from the first pharyngeal arch. Upon contraction the anterior belly of the digastric muscle elevates the hyoid bone. The anterior belly of the digastric is innervated by the mylohyoid nerve, which arises from the mandibular division of the trigeminal nerve (CN V3).

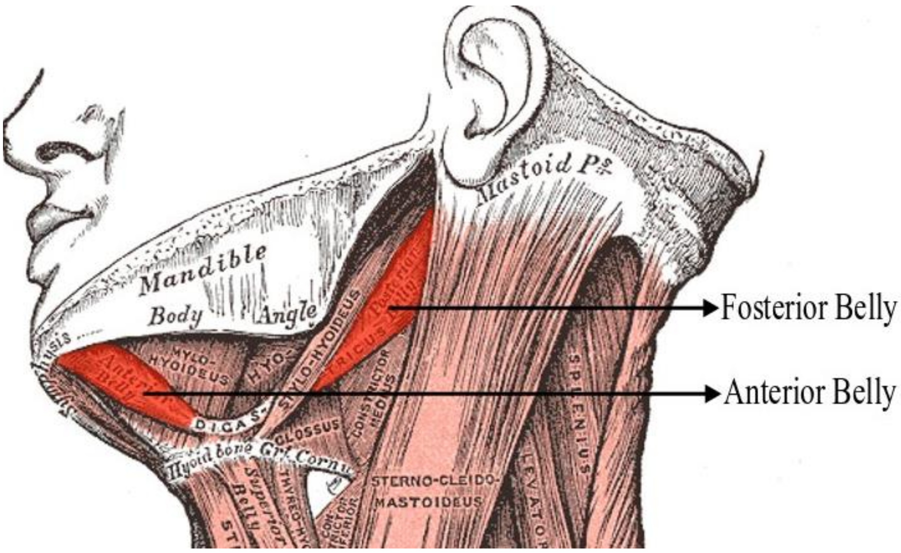

Figure 3-3*:* Anterior and Fosterior Belly of Digastric

3.2 Mathematical Modeling

3.2.1 Differential Mode

Differential amplifier is the amplifier which amplifies the difference between the two input signals. In an ideal differential op-amp, the output signal Vout is given by

$$V_{out} = A_d(V_1 - V_2) \quad 3.2.1$$

Where, V_1 = input in non-inverting terminal

V_2 = input in inverting terminal

A_d = Differential gain of op amp

From the above equation it is clear that for ideal op amp, any signal common to both the inputs have no effect on the output. This is known as common mode rejection. In non-ideal op amps output depends not only on differential input (Vd) but also on common mode signal (Vc).

$$V_d = (V_1 - V_2) \quad 3.2.2$$

$$V_c = \frac{(V_1 + V_2)}{2} \quad 3.2.3$$

Let Ad denotes differential gain of op amp and Ac denotes its common mode gain then the common mode rejection ratio (CMRR) of a differential amplifier is calculated as

$$\text{CMRR} = \left|\frac{Ad}{Ac}\right| \quad 3.2.4$$

$$\text{CMRR} = 20\log\left|\frac{Ad}{Ac}\right| dB \quad 3.2.5$$

CMRR depends on a number of design choices within the amplifier, but basically depends on the loop gain of the amplifier. With high loop gain, the error signal across the input terminals of the op amp is driven to zero and CMRR is high. At low frequency where the loop gain is high, the error signal is very low and CMRR is high. With low loop gain, the error signal across the input terminals of the op amp is high and CMRR is low. As frequency increases and loop gain decreases, the error signal across the input terminals of the op amp increases. The larger error signal across the input terminals of the op amp intern leads to lower CMRR. [14]

3.2.2 Bandwidth of an Operational Amplifier

Real op amps cannot operate in all frequency ranges as they have finite bandwidth. Let A_0 be the open-loop gain of an op amp and w_0 be the cut-off frequency of the op amp then the open loop voltage-gain transfer function of the op amp is given by

$$\mathrm{A(s)} = \frac{A_O}{1 + \frac{s}{w_O}} \qquad 3.2.6$$

$$\text{Or, } \mathrm{A(jw)} = \frac{A_O}{1+\frac{jw}{w_O}} \qquad 3.2.7$$

$$\text{Or, } |\mathrm{A}| = \frac{A_O}{\sqrt{1+\left(\frac{jw}{w_O}\right)^2}} \qquad 3.2.8$$

For frequencies much greater than $w_0 = 2\pi f_0$, $w >> w_0$ open loop gain of op amp scales as

$$|\mathrm{A}| = \frac{A_O}{\sqrt{1 + \left(\frac{jw}{w_O}\right)^2}} \qquad 3.2.9$$

$$\text{Or } |\mathrm{A}| = A_O\left(\frac{w_O}{w}\right) \qquad 3.2.10$$

$$\text{Or } |\mathrm{A}|\mathrm{f} = A_O f_O \qquad 3.2.11$$

Where, $A_0 f_0$ is Gain-Bandwidth Product (GBP)

Thus, the product of open-loop gain and bandwidth of an op amp is constant which is known as Gain-Bandwidth Product (GBP). This product is given in the manufacturer dataset for each op amp and sometimes is denoted as "unity gain bandwidth". [15]

3.2.3 Butterworth Filter

Butterworth filter is a signal processing filter designed to have a frequency response as flat as possible in the passband i.e. ideally no ripples in the pass band. The transfer function of an ideal n-order Butterworth filter is given by

$$or, |T_n(\mathrm{jw})^2| = \frac{1}{\left(1+\frac{w_0}{\mathrm{w}}\right)^{2\mathrm{n}}} \quad 3.2.12$$

Where, w_c = cut-off frequency of filter

The frequency response of the Butterworth filter is obtained from above equation which is as shown in figure below

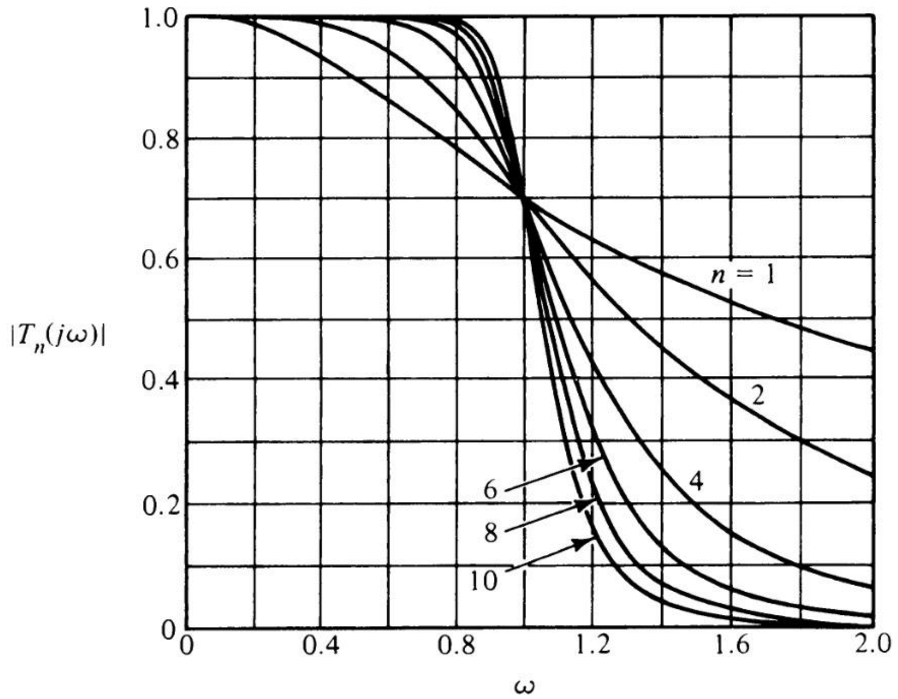

Figure 3-4: Frequency response of different orders of Butterworth filter

The attenuation (A) introduced by a Butterworth filter is given by

$$\mathrm{A} = 20\log|\mathrm{T(jw)}|dB \quad 3.2.13$$

For the pass band extending from w = 0 to w = w_p the attenuation should not exceed Amax. From w_p to w_s we have a transition band and for a stop band beyond w_s the attenuation should not be less than A_{min}.

The order of a Butterworth filter with maximum attenuation for passband (A_{max}), minimum attenuation for stop band (A_{min}) is calculated using the following equation

$$T(jw) = \frac{T_0}{\left[1 + \varepsilon^2 \left(\frac{w_s}{w_p}\right)^{2n}\right]} \qquad 3.2.14$$

Where, ε = maximum pass band gain
w_s = stop band frequency
w_p = pass band frequency

The order of the Butterworth filter also determines its roll-off characteristics. For a Butterworth filter of order 'n' the roll-off rate is 20n dB/decade or 6n dB/octave. The design and circuit implementation of such higher order Butterworth filters with all the above parameters can be done in different filter design topologies such as Cauer topology, Sallen and Key topology, etc. [16]

3.2.3.1 High Pass Filter

High-pass filter passes signals above cut-off frequency (fc) and attenuates signals lower than the cut-off frequency. Based on the design requirements the order of a Butterworth high-pass filter can be determined from equation 3.2.19. General high-pass passive filter of the second order is as shown in figure below.

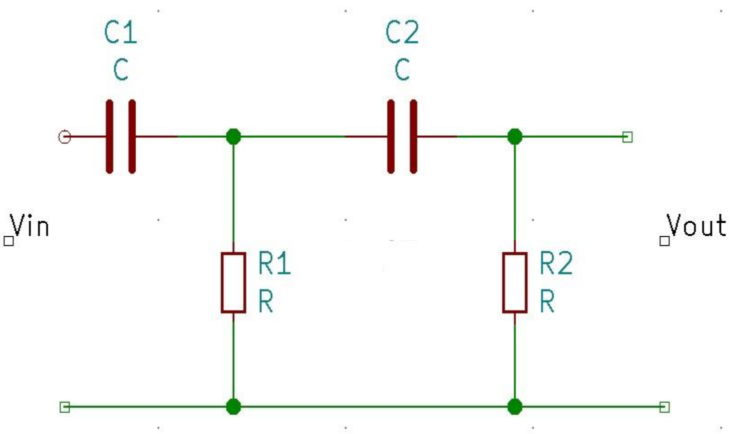

Figure 3-5: Second order Passive Butterworth HPF

The cut-off frequency of the above filter circuit is given by

$$f_c = \frac{1}{2\pi\sqrt{R_1 R_2 C_1 C_2}} \qquad 3.2.15$$

Let $R_1 = R_2 = R$ and $C_1=C_2=C$ the above equation simplifies into

$$f_c = \frac{1}{2\pi RC} \qquad 3.2.16$$

The value of C is determined as per the choice or given cut-off frequency and the corresponding value of R is determined from the above equation.

3.2.3.2 Low Pass Filter

Low-pass filter passes signals below cut-off frequency (fc) and attenuates signals higher than the cut-off frequency. Based on the design requirements the order of a Butterworth low-pass filter can be determined from equation 3.2.21. Sallen and Key topology of active analog filter design is very common in practice. Basic 2nd order LPF based on this topology as shown in figure below.

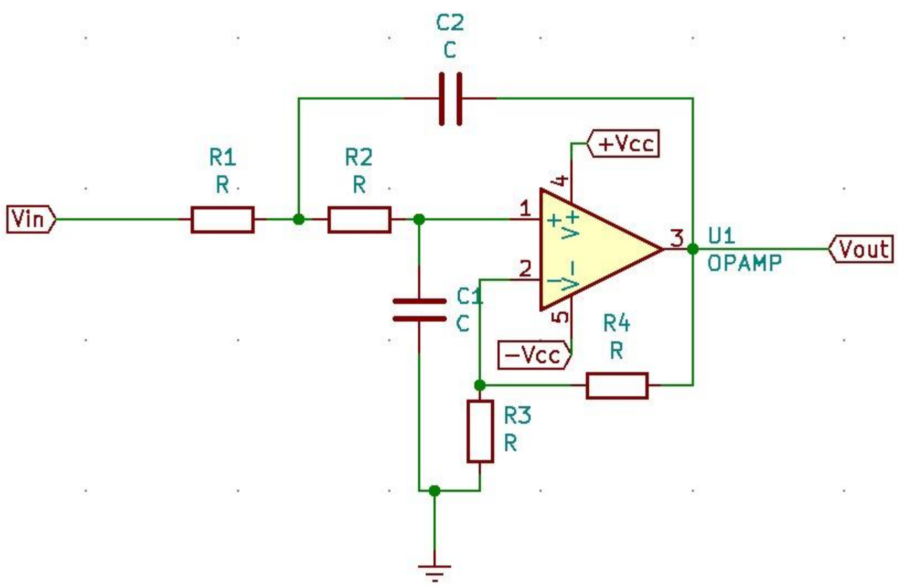

Figure 3-6: General second order Sallen-Key LPF

The transfer function of the above circuit is given by

$$\mathrm{A(s)} = A_0/1 + w_c\{C_1(R_1 + \mathrm{R2}) + (1 - A_0)R_1C_2\}\mathrm{s} + {W_C}^2R_1R_2C_1C_22S^2 \quad 3.2.17$$

Where, wc is the cut-off frequency

Since $R_1 = R_2 = R$ and $C_1 = C_2 = C$ we have

$$\mathrm{A(s)} = A_0/[1 + w_c\mathrm{RC}(3 - A_0)s + (w_cRC) \quad 3.2.18$$

$$A_0 = 1 + \frac{\mathrm{R4}}{\mathrm{R3}} \quad 3.2.19$$

Let us consider,

$$\mathrm{a} = w_cRC(3 - A_0) \quad 3.2.20$$

$$\mathrm{b} = (w_cRC)^2 \quad 3.2.21$$

The value of C is set as per the choice and the corresponding values of R and A_0 is determined using the following equations.

$$\mathrm{R} = \sqrt{b}/2\pi \mathrm{f}_c\mathrm{C}) \quad 3.2.22$$

$$\mathrm{A}_0 = 3 - (\frac{\mathrm{a}}{\sqrt{b}}) \quad 3.2.23$$

$$\mathrm{A}_0 = 3 - \frac{1}{\mathrm{Q}} \quad 3.2.24$$

Where, Q = pole quality of the filter

4. SIGNAL ARTIFACTS AND NOISE

Noise is any unwanted disturbance that hinders or interferes with a desired signal. To put it differently, everything that is not part of the signal wanted to be measured is considered noise. However, a differentiation can be made between disturbances or interferences and the word noise. Disturbances often come from sources external to the circuit under study, and result from electromagnetic or electrostatic coupling with the power lines, fluorescent lights, cellphones and cross-talk between adjacent circuits, even mechanical vibration could also cause disturbances. Most of these types of disturbances and possible sources of interference are “man-made” and can be minimized or eliminated.

4.1 Types of Noise

The identity of an actual EMG signal that originates in the muscle is lost due to the mixing of various noise signals or artifacts. The attributes of the EMG signal depend on the internal structure of the subject, including the individual skin formation, blood flow velocity, measured skin temperatures, the tissue structure (muscle, fat, etc.), the measuring site, and more. These attributes produce different types of noise signals that can be found within the EMG signals.

4.1.1 Electrode Noise

Electrode noise occurs due to the electrolyte–skin and electrolyte–metal interfaces. Once the electrolyte–metal electrochemical reaction stabilizes, this source of noise is negligible (0.3 μV P-P). The amplitude of the electrolyte–metal noise for Ag-AgCl electrodes decreases dramatically within the first minute of application and stabilizes. The electrolyte-skin interface is more problematic. The noise voltage can range from 5 to 60 μV P-P.

The elimination of such noises can be achieved with good skin preparation (but it is subject dependent) and using specific types of electrolyte for the specific type of electrode.

4.1.2 Inherent Noise

The amplitude of EMG is random in nature. EMG signal is affected by the firing rate of the motor units, which, in most conditions, fire in the frequency region of 0 to 20 Hz. The numbers of active motor units, motor firing rate and mechanical interaction between muscle fibers can change the behavior of the information in the EMG signal. This kind of noise is considered as unwanted, and the removal of the noise is important.

4.1.3 Cross-Talk

Cross-Talk refers to the signal that is detected over a certain muscle but is generated by another, mostly nearby muscle. It is mostly prevalent in surface electrodes where the distance of the detection points from the sources is of the same order of magnitude for the sources in different muscles.

Crosstalk also depends on the many physiological parameters, and can be minimized by choosing electrode size and inter-electrode distances (typically 1–2 cm) carefully which actually improves the selectivity of the electrodes.

4.1.4 Movement Artifacts

It is vital to maintain a steady and secure connection at the skin-electrode interface to eliminate any artifact associated with the movement of cables and displacement of electrodes. Movement artifacts cause irregularities in the signal. This can be reduced by proper design of the electronic circuitry and maintaining proper set-up.

4.1.5 ECG Artifacts

EMG signal extract is bound to be contaminated by the electrical activity from the heart. The placement of EMG electrodes, which is conducted by a selection of the pathological muscle group, often decides the level of ECG contamination in EMGs. Due to an overlap of frequency spectra by ECG and EMG signals and their relative characteristics, it is very difficult to remove the ECG artifacts from the EMG signal.

ECG contamination in EMGs may be kept at a minimal level by common-mode rejection at the recording site, by the careful placement of bipolar recording electrodes along the heart's axis if possible. The electrode placement in our proposed design is mostly focused on muscles relating to speech and are localized at the facial region and thus not very susceptible to ECG artifacts.

4.1.6 Electromagnetic Noise

The human body behaves like an antenna—the surface of the body is continuously inundated with electric and magnetic radiation, which is the source of electromagnetic noise. Electromagnetic sources from the environment superimpose the unwanted signal, or cancel the signal being recorded from a muscle. The amplitude of the ambient noise (electromagnetic radiation) is sometimes one to three times greater than the EMG signal of interest.

The dominant concern for the ambient noise arises from the 50 Hz radiation from power sources, which is also called line noise. This is caused by differences in the electrode impedances and in stray currents through the patient and the cables. However, in order to remove the recorded artifact, off-line processing is necessary. Line noise (n(t)) with its harmonics can be mathematically represented as:

$$n(t) = cos(2\ 50t) + cos(2\ 100t) + cos(2\ 200t) + cos(2\ 300t) \qquad 4.1.1$$

A number of adaptive filter techniques have been proposed for the attenuation of the line noise, such as adaptive FIR notch filter, adaptive IIR notch filter, adaptive notch filter using Fourier transform and so forth. These filters improve the SNR of an EMG signal by eliminating the line noise from the system.

5. INSTRUMENTATION AND REQUIREMENT ANALYSIS

5.1 Hardware

5.1.1 Electrodes

An electrode is a solid electric conductor through which an electric current enters or leaves an electrolytic cell. It is simply a transducer that converts ionic potentials to electric potentials. There exist two main types of electrodes for the extraction of EMG signals from the body. They are:

5.1.1.1 Surface Electrode

Surface electrodes are non-invasive electrodes placed on the skin directly over the muscle for measurement and detection of EMG signal. These electrodes are simple and very easy to implement and do not require medical supervision and certification. It is designed to selectively obtain the surface EMG signal while minimizing the artifacts, DC potentials and environment noise picking.

Working Principle:

The theory behind the working of surface electrodes is that they form a chemical equilibrium between the detecting surface and the skin of the body through electrolytic conduction, so that current can pass from an electrolyte to a non-polarized electrode oxidizing the electrode atoms. The resulting cations and electrons flow in opposite directions: the electrons go through the metal cables attached to the electrodes meanwhile the cations go to the electrolyte. However, use of proper electrolytes with respective electrodes should be ensured for the electrolytic conduction to occur.

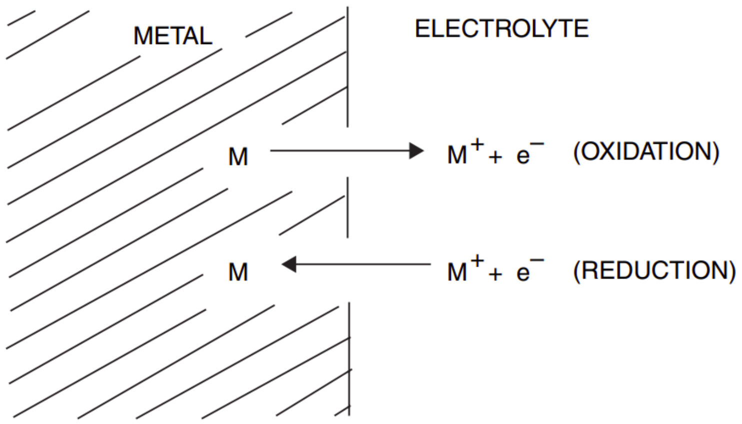

Figure 5-1: Electrode-electrolyte Interface [17]

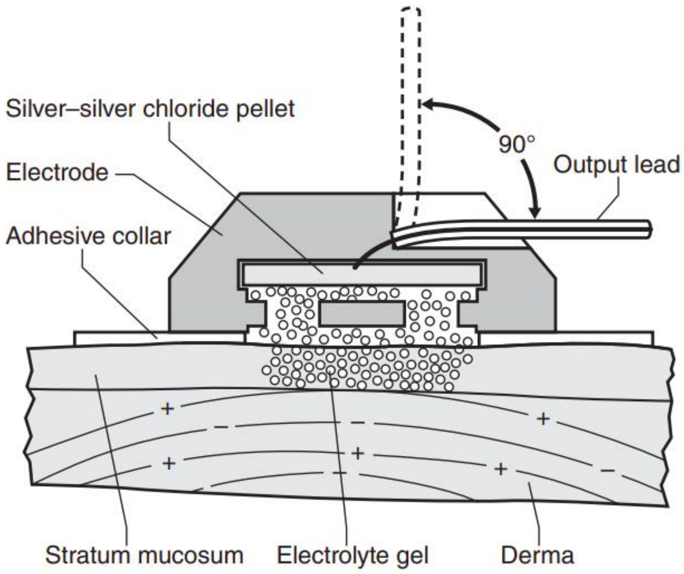

Figure 5-2: Skin-Electrode Interface (Ag-AgCl electrodes) [11]

When the electrochemical reaction between the metal and the electrolyte stabilizes, a potential difference known as "half-cell potential" is formed between the negative electrode and the positive electrolyte which is determined by the Nernst equation as:

$$E = \frac{RT}{nF} \ln \left(\frac{a_1}{a_2}\right) \tag{5.1.1}$$

Where, a1 and a2 are ionic activities on each side of the membrane

E= half-cell potential

R= universal gas constant = 8.314 Joule per mole per kelvin

T= absolute temperature

n= the number of valence electrons in the metal

F= Faraday Constant = 96485 C per mole

The half-cell potential of a single electrode results in a direct current (DC) offset in EMG signal. If two chemically identical electrodes make contact with the same electrolyte/body, the two interfaces should, in theory, develop identical half-cell potentials. When connected to a differential amplifier, the half-cell potentials of such electrodes would cancel each other out and the offset voltage would be zero. The electrode potentials would, therefore, make zero contribution to a biosignal they were being used to detect. Unfortunately, slight differences in electrode metal or gel result in the creation of offset voltages, which can greatly exceed the physiological variable to be measured. Generally, a more significant problem is that the electrode offset voltage can fluctuate with time, thus distorting the monitored biosignal.

The skin, gel, and electrode interfaces function as a complex physical system that is frequency dependent and affects the EMG signal in a deterministic way. It represents a complex impedance that can be modeled as a capacitor (C1) in series with a resistor (R1). This impedance may vary from a few kilo-ohms to a few mega-ohms, depending on electrode size and skin condition. There is an additional resistor (R2) in parallel to denote the resistance of the chemical reaction (activation energies) that moves the charge at the interface to accurately model the skin-electrode interface.

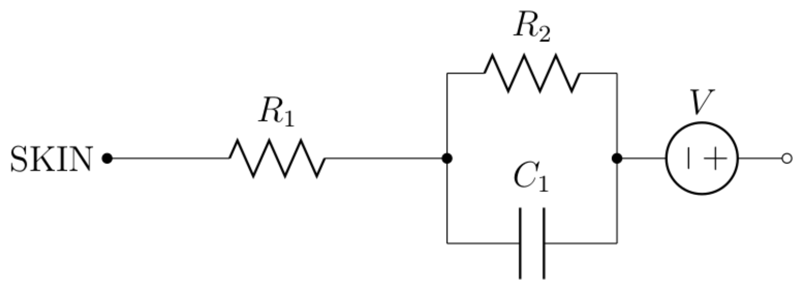

Figure 5-3: Skin-Electrode Circuit Model [17]

Where, V= half-cell potential

C1= the capacitive effects of the electrolyte dipole layer at the electrode surface

R1= bulk resistance of the electrolyte gel

R2=the resistance of the chemical reaction (activation energies) that moves the charge at the interface

Surface electrodes are usually made up of silver/silver chloride (Ag-AgCl), silver chloride (AgCl), silver (Ag) or gold (Au) or platinum (Pt). Surface area, utility, selectivity, sensitivity and many other parameters vary with the type of material used in the electrode. Selecting the proper type of electrodes that can result in having low electrode-skin impedance and can last longer for recording is important for EMG measurements.

Surface electrodes can be either polarizable or non-polarizable. The electrode where no actual charge crosses the electrode-electrolyte interface when a current is applied is a polarizable electrode. The current across the interface is a displacement current and the electrode acts like a capacitor. The electrode where the current passes freely across the electrode-electrolyte interface without any external energy to make the transition is a non-polarizable electrode. Platinum electrode is an example of polarizable electrode whereas Ag-AgCl electrode is an example of non-polarizable electrode.

Silver−Silver Chloride Electrodes:

Ag-AgCl electrodes are electrodes with a thin layer of silver coating on plastic substrates and the outer layer of silver is converted to silver chloride. Some of the important characteristic of Ag-AgCl electrodes are:

- Low half-cell potential of about 220 mV
- High conductivity of 6.30×10^7 Siemens per meter at 20℃
- High exchange current density of 10A/cm
- Low level of intrinsic noise
- Low contact impedance

Electrodes made of Ag-AgCl are often preferred over the others, as they are almost non-polarizable electrodes, which means that the electrode-skin impedance is resistive and not capacitive. Low half-cell potential results in low DC offset in recordings and small redox potential facilitates the easier and fast exchange of ions. Therefore, the surface potential is less sensitive to relative movements between the electrode surface and the skin. Additionally, these electrodes provide a highly stable interface with the skin when electrolyte solution is interposed between the skin and the electrode. Such a stable electrode-skin interface ensures high signal to noise ratios, reduces the power line interference in bipolar derivations (50 Hz or 60 Hz frequencies and their harmonics) and attenuates the artifacts due to body movements.

Gold Electrodes:

Gold electrodes are electrodes with a thin layer of gold coating on metals like silver or copper. Some of the important characteristic of gold electrodes are:

- Half-cell potential of about 1.680 V
- Has high conductivity of 4.1×10^7 Siemens per meter at 20℃
- Higher contact impedance than Ag-AgCl
- Although expensive, they are reusable and durable
- High immunity to external noises

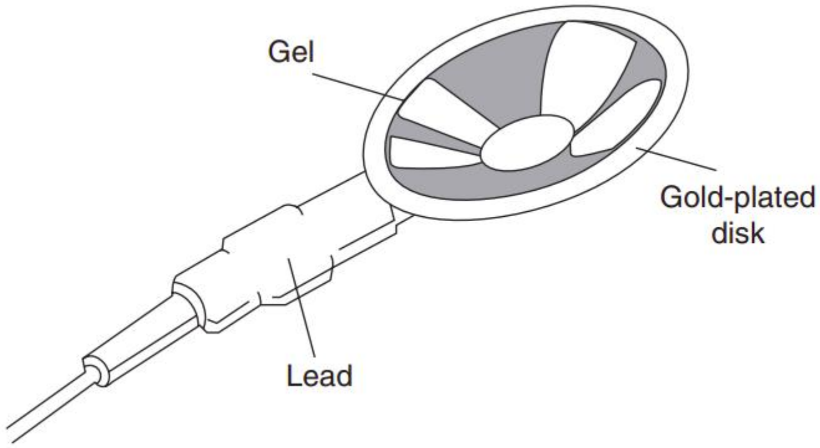

Figure 5-4: Gold Plated Cup Electrodes [18]

Typically, gold plated EMG electrodes have a 1.45 mm diameter conductive area on a disc of 10 mm. Smaller area provides high selectivity and thus is suitable for detection of EMG signals of a localized area or an individual muscle tissue.

5.1.1.2 Indwelling Electrode:

Indwelling electrodes are invasive electrodes inserted through the skin directly over the muscle. Needle electrodes and fine wire electrodes are two commonly used indwelling electrodes used to measure action potential of a motor unit directly. Indwelling electrodes have two main advantages. One is that its relatively small pickup area enables the electrode to detect individual MUAPs during relatively low force contractions. The other is that the electrodes may be conveniently repositioned within the muscle (after insertion) so that new tissue territories may be explored. However, better selectivity and crosstalk immunity of indwelling electrodes comes at a price. They are painful and carry the risk of infections.

This project utilizes Ag-AgCl electrodes due to the cheaper cost and its easier availability and convenience in the usage.

5.1.2 Electrode Leads

Electrode leads are any set of wires that has the sole responsibility to transfer the charges induced on the electrodes to a signal acquisition system which has an amplifier (normally an Instrumentation Amplifier) at the front end. Simply, electrode leads are specialized cables designed to conduct electrical signals with minimum losses and distortion. Since signal from the electrode is fed to the amplifier through electrode leads, they are also termed as input leads. As the input leads offer a finite resistance, there will be some degree of voltage drop between the electrodes and amplifier resulting in loss of signal.

From ohm's law,

$$V(drop) = I(cable) \times R(cable) \qquad 5.1.2$$

Resistance is a function of the conductivity of the material (σ), length (l), and Surface area (A):

$$R = lA \qquad 5.1.3$$

Of these three factors, length is the most critical because it can change to the greatest degree and is under our control. Keeping the length of the input leads and all cables as short as possible will minimize the voltage drop.

A signal amplitude (V_{in}) is attenuated to differential voltage at the amplifier (V_{out}) by the electrode leads. Thus, the Attenuation (A) can be calculated as:

$$A = -20 \log\left(\frac{Vout}{Vin}\right) \qquad 5.1.4$$

The most sensitive part in the EMG system design is the path between the electrodes and the amplifier because it is where the EMG signal has the lowest voltage level and is most vulnerable to noise and interference pickup. The longer the signal has to travel, the more interference and noise get coupled electromagnetically. EMG signal for our intended purpose varies from 1 Hz to 500 Hz in frequency and is not susceptible to attenuation loss due dielectrics at high frequencies (above 1Mhz). However, electromagnetic interference does occur and hinders the quality of propagating signal. This can be avoided by the use of shielded cables.

Shielded cables are composed of three layers. A signal-carrying conductor at the center is covered by a flexible insulating layer, which is then surrounded by a braided metal sheath. Shielded cable acts as a Faraday cage to reduce electrical noise from affecting the signals. It also minimizes capacitively coupled noise from other electrical sources.

Electrode Configuration

Electrode configuration refers to the number of recording surfaces and their arrangement relative to muscle, tendon and bony surface. The two most common methods are:

A. Monopolar

Monopolar uses three electrodes E1, E2 and Ground. E1 is placed over the muscle itself where the EMG signal is to be extracted and also referred to as "active recording surface electrode". E2 is placed on an electrically neutral location such as tendon and also referred to as "reference electrode" and Ground is placed on a bony surface distant to E1 and E2. This configuration is called monopolar because only one electrode (E1) is used to record the muscle activity.

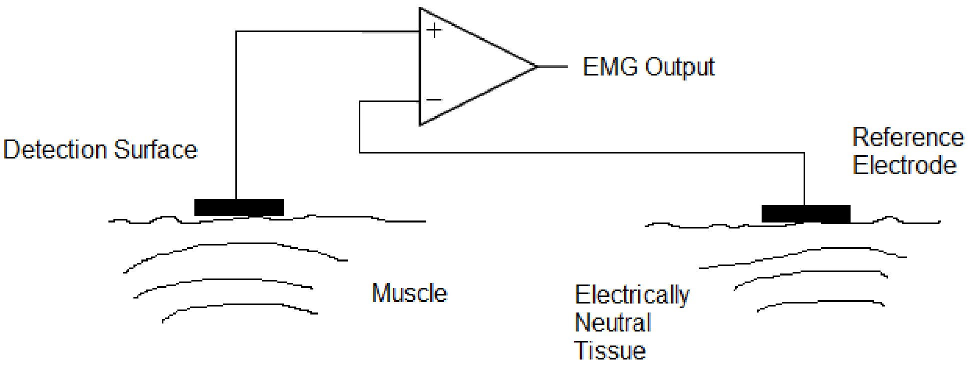

Figure 5-5: EMG Signal Extraction in Monopolar Configuration [19]

For monopolar configuration, select muscle on the skin surface where the lowest possible electrical stimulation will produce a minimal muscle twitch. The main drawback of this configuration is that it does not take full advantage of the differential amplifier design to reduce the unwanted noise in the EMG recordings.

B. Bipolar

Bipolar also uses three electrodes E1, E2 and Ground. E1 and E2 are placed over the muscle at a certain distance of about 5 to 20 mm apart. Ground is placed on a bony prominence typically near E1 and E2.

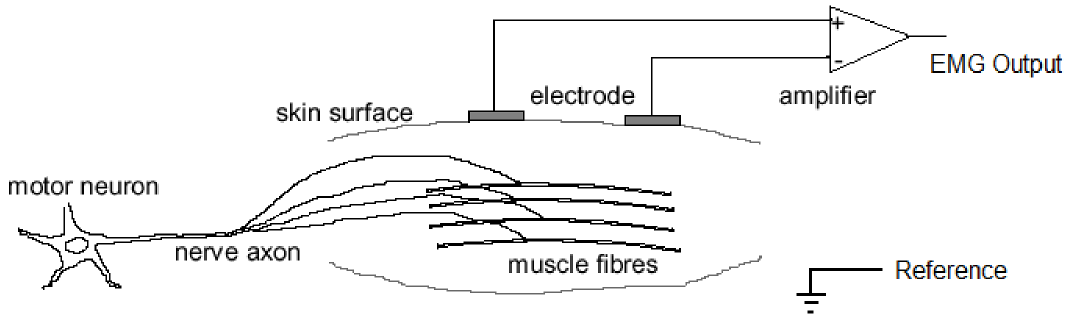

Figure 5-6: EMG Signal Extraction in Monopolar Configuration [22]

For bipolar configuration, select a large enough muscle on the skin surface with lowest possible movement. This method overcomes the shortcoming of monopolar by taking the full advantage of amplifier circuitry that is designed to minimize unwanted interference signals from electromagnetic fields in the surrounding environment. However, the amplitude and frequency is largely dependent on the inter-electrode distance which sometimes is not easy to work with.

5.1.3 Amplifier

Instrumentation amplifiers amplifies the weak signal from the muscles and make it detectable for the microcontroller which extract the data and send it for further processing. The voltage signal is of a magnitude range of 10 microvolts, which is very small for filtering and feeding to ADC. The instrumentation amplifier is a type of differential amplifier that eliminates the use of input impedance matching also rejects superimposed noise and interference noise. It provides very low DC offset voltage, low noise, very high open-loop gain, very high common mode rejection ratio (CMRR) and very high input impedance. AD620 has a bandwidth of 120 KHz with a gain range of 1 to 1000, settling time of 15 µs and 100 dB min Common-Mode Rejection Ratio (CMRR). The response of CMRR and gain of AD620 with respect to frequency is as shown in the figures below.

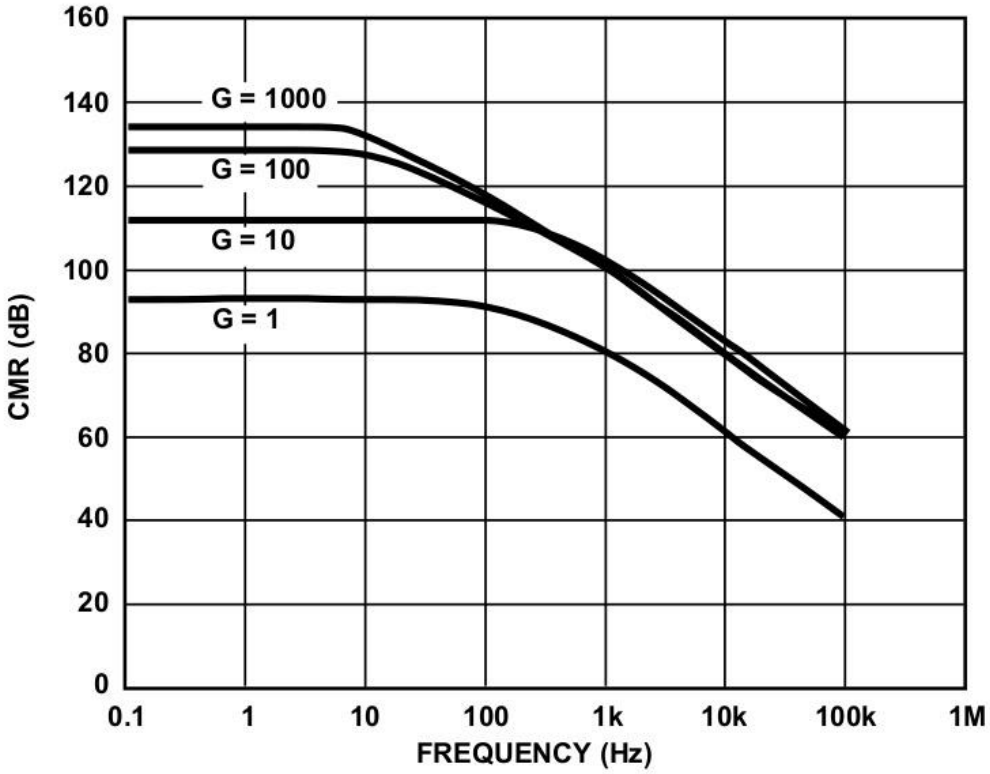

Figure 5-7: Typical CMRR vs. frequency curve of AD620 [20]

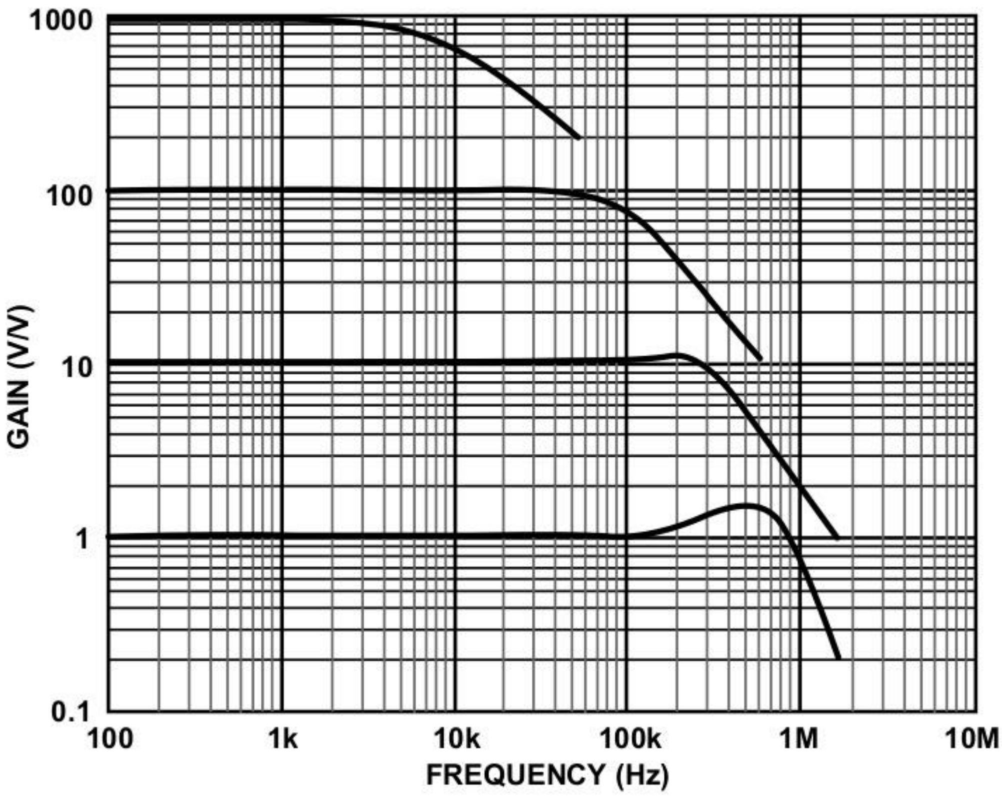

Figure 5-8: Voltage Gain Vs. frequency curve of AD620 [20]

AD620 and OP37AJ amplifier ICs are used along with resistors and capacitors for signal amplifying and filtering. The signal is first pre-amplified with AD620 instrumentation amplifier and low frequency noise is eliminated. Using filter after 1st stage amplification blocks low noises on further amplification. Amplifier OP37AJ amplifies the signal to higher strengths and then low pass filter is introduced to reject high frequency noises. Finally another OP37AJ amplifier amplifies the signal to produce output in the level of volts. Gain of amplifiers and frequency of filters can be set using resistors and capacitors, which provides flexibility for similar kinds of varying signals. [9]

The response curve of amplifier OP37 is as shown in the figure below.

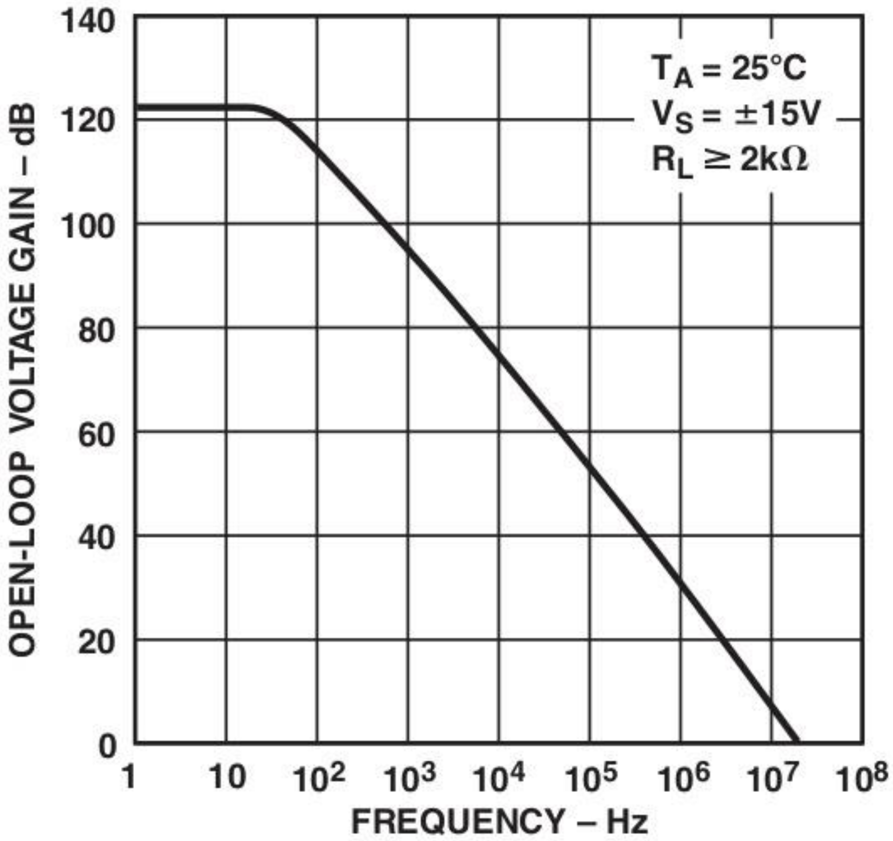

Figure 5-9: Frequency response of OP37 [21]

5.1.4 Filter

EMG signals have wide range of frequency ranging from 1 Hz to 5,000 Hz [11]. However, the desired articulated EMG signals ranges from 1 Hz to 100 Hz which is associated with noises such as line noise, ECG artifacts, cross-talks, blood flow in the muscles, aberrant signals from the central nervous system and so on. Thus a suitable band pass filter needs to be designed having cut-off frequencies at 1 Hz and 100 Hz. That said, the output response of the filters other than Butterworth filter contains ripples in the pass band which distorts the overall output of the filter. In expense of the flattest response of the pass band, it has a wide transition band. To overcome this drawback, the roll-off factor needs to be higher which ultimately implies higher filter order which can be calculated as given by the equation 3.2.14.

Along with the selection of the pass band, significant attenuation also occurs in passive filters. Active filters, in other hand, provide gain to the signal along with filtration which is most suitable for low frequencies. Band pass filtration is achieved cascading a passive high pass for higher frequencies and an active low pass filter for lower frequencies.

5.1.5 Arduino

The signal obtained is in analog form which needs to be converted to digital using the in-built ADC of Arduino. It consists of a 6 channel ADC with a resolution of 10 bit. The type of ADC in Arduino is Successive Approximation Register (SAR) which maps input voltage between 0 to 5 volts into integer values between 0 and 1023 but does not sample the samples in negative domain.

5.1.6 Bluetooth Modules

HC-05 module is an easy to use Bluetooth Serial Port Protocol module, designed for transparent wireless serial connection setup through serial port. It is a fully qualified Bluetooth V2.0+ module that has enhanced data rate of 3 Mbps with complete 2.4 GHz radio transceiver and baseband. It uses CSR BlueCore-04 External single chip Bluetooth system with CMOS technology and with Adaptive Frequency Hopping Feature implemented in the available 79 different channels.[22]

5.2 Software

5.2.1 Arduino IDE

The Arduino IDE is a cross-platform application that is written in functions from C and C++. It is used to write and upload programs to Arduino compatible boards but also, with the help of third-party codes, other vendor development boards. The source code for IDE is released under the GNU (General Public License).

5.2.2 Python

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together.

Python is used for data processing. Python has provided libraries like pyEEG, pySpACE, bioSPPy for pre-processing of signals. These libraries can be used for signal classification. Further processing of signal is done by using Neural Network in python. The voltage signal in the digital form is analyzed to predict the possibility of a letter that the person is articulating.

5.2.3 KiCad

KiCad is a free software suite for electronic design automation (EDA). It facilitates design of schematics for electronic circuits, converting them to printed circuit board (PCB) designs along with circuit simulation. It has built-in footprints of different electronic components. Footprint of new components can also be designed manually.

6. SYSTEM ARCHITECTURE AND METHODOLOGY

6.1 System Block Diagram

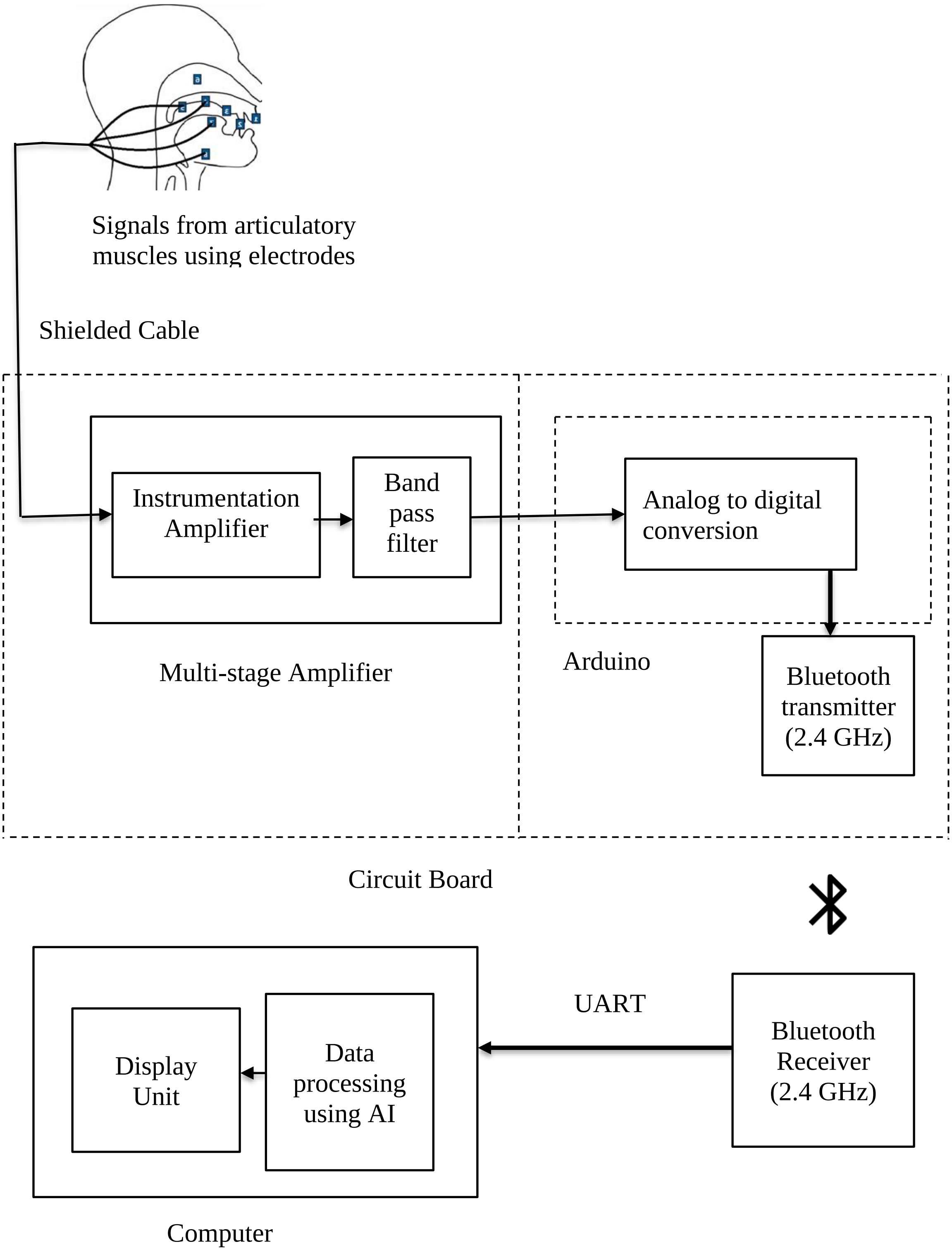

Figure 6-1: System Block Diagram

6.2 Electrode Placement and Signal Extraction

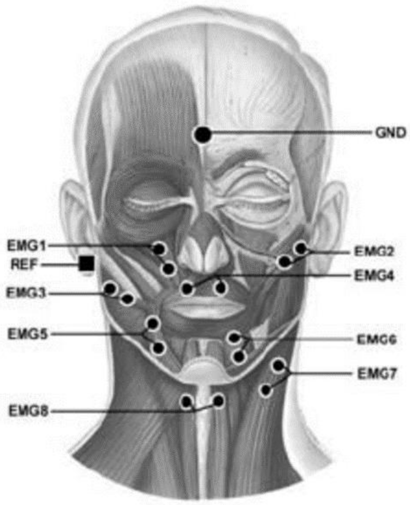

Figure 6-2: Placement of Electrodes

The electrode placement on the muscles was based on the theoretical analysis which is as shown in the figure 6-2. The signals from the Ag-AgCl electrodes placed on the channels EMG1 and EMG2 were extracted and fed to the next stage as shown in the figure 6-1. [23]

6.3 Signal Amplification and Filtering

The amplification and filtering of the signal that is extracted from the articulatory muscles is performed in the multi-stage amplifier block. Further classification of the block is shown in figure 6-3. The instrumentation amplifier AD620 amplifies the signal obtained from electrodes with low noise and high CMRR. The output is then fed to the second order high pass filter. As this filter has a cut-off frequency at 1 Hz, only the signals above 1 Hz are passed while other signals are filtered out. The signals are then forwarded to the input of amplifier OP37 which amplifies the signal with a calculated gain. The signal is finally passed to the second order low pass active filter having cut-off frequency at 100 Hz. This block passes the signals below 100 Hz along with their amplification. Thus, as a whole, the high pass and low pass filter in cascade give a response equivalent to a band pass filter with pass band of 1 Hz to 100 Hz.

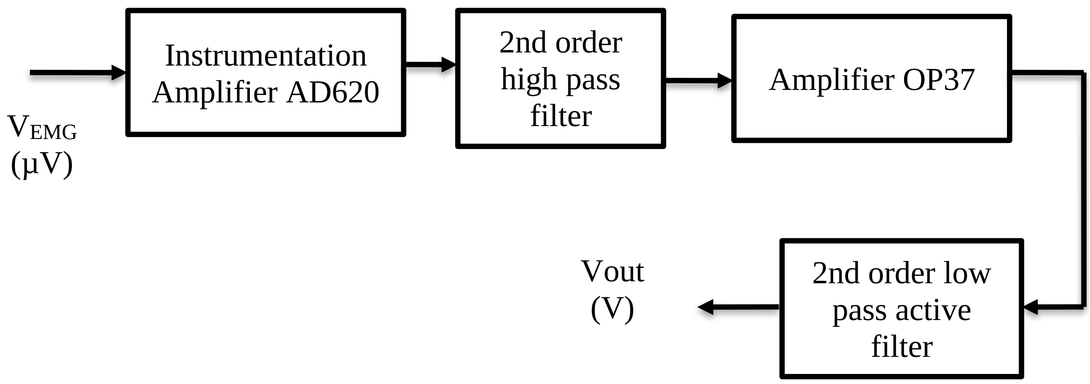

Figure 6-3: Block diagram of Amplifier and Filter

6.4 Analog to Digital Conversion

The signal obtained from the multi-stage amplifier section is in analog form. This ADC block converts the analog signal to digital signal. The ADC samples the data at the sampling frequency of 200 Hz. It maps input voltage from 0 to 5 volts into integer values between 0 and 1023.

6.5 Bluetooth Communication

The digitized signals are required to be transmitted to a PC for further processing. Bluetooth transmitter transmits the data wirelessly to a Bluetooth receiver at 2.4 GHz. The data from the Bluetooth receiver is then transferred to the computer using USB protocol and further processing is done in the computer.

6.6 Extraction of Signal Features

After the EMG signal is received by a remote computer, the signals need to be processed to extract the actual data contained in a multi-channel EMG signal. Since EMG signal is very different from the speech signal, it is necessary to explore feature extraction methods that are suitable for EMG to text conversion. Many techniques can be followed for extracting features suitable for this specific project which can be described as follows:

6.6.1 Windowing

Windowing splits any input signal into sufficiently small segments such that the properties of the signal does not have time change within that segment. Windowing does thus change the signal, but the change is designed such that its effect on signal statistics is minimized. Windowing in signal analysis is mostly focused on extracting information as accurately as possible. Since the windowing process reduces the time domain information, resolution in the frequency domain is reduced which implies that there is reduced leakage of spectrum. Thus, before extracting any features in frequency domain, the time variant data is windowed.

6.6.2 Wavelet Transform

Wavelet transform is a mathematical tool that serves mainly for data analysis of non-stationary and fast transient signals in both time and frequency domains. The EMG signals can be considered as the sum of scaled delayed conversions of a single prototype. The most common methods to determine the frequency spectrum of EMG signals are fast Fourier transform (FFT) and short time Fourier transform (STFT). The coefficients of the signals from FFT and STFT can be extracted and fed to the neural network. Besides these there are many wavelets transforms such as short Fourier transform (SFT), Cohen class transformation, Wigner-Ville distribution, Dual Tree complex wavelet transform (DTCWT), and so on.

6.6.3 Autoregressive Model

Autoregressive (AR) model is a great tool to develop a technique for estimating intramuscular EMG and their spectral properties from surface measurement. The input data is transformed using AR transform and the AR coefficients of the signal are determined from the transformation.

6.7 Architecture of Neural Network

After the extraction of features, they need to be fed to a recognition modal which classifies the features to their corresponding word (or letter) labels.

A work done by Arnav Kapur and his team has employed a 1-dimensional convolutional network to accomplish this. Their model architecture incorporates the hidden layer which convolves 400 filters of kernel size 3 with stride 1 with the processed input and is then passed through a rectifier nonlinearity. This is subsequently followed by a max pooling layer. This unit is repeated twice before globally max pooling over its input. This is followed by a fully connected layer of dimension 200 passed through a rectifier nonlinearity which is followed by another fully connected layer with a sigmoid activation.

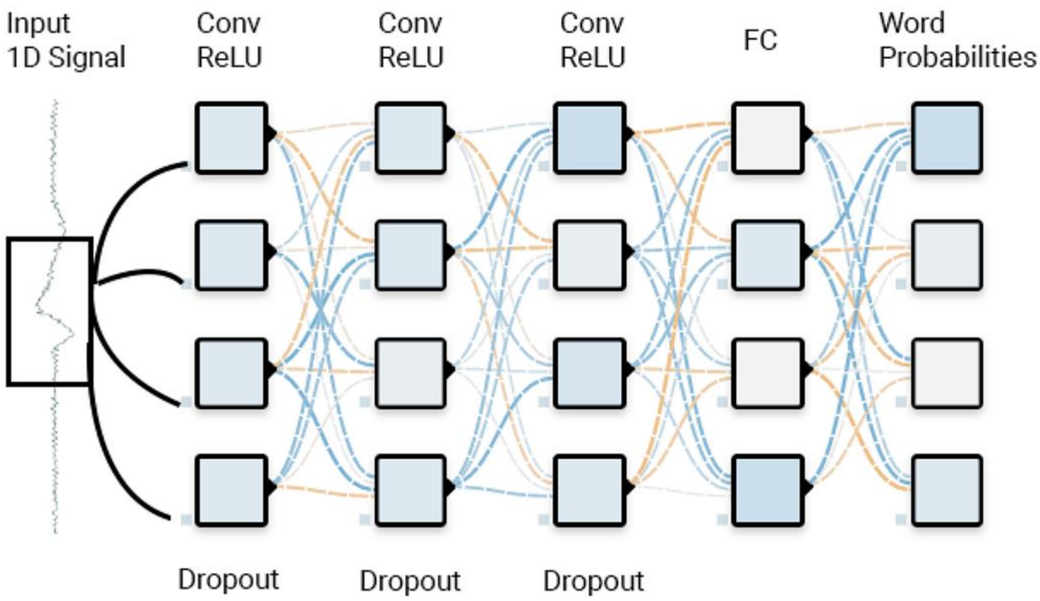

Figure 6-4: Architecture of the AlterEgo silent speech recognition model

The network was optimized using a first order gradient descent and parameters were updated during training. The network was regularized using a 50% dropout in each hidden layer to enable the network to generalize better on unseen data. The error during training was evaluated using a cross entropy loss. The neural network was trained on a single NVIDIA GeForce Titan X GPU. [3]

In another study by Pol Rosello and his team on “End-to-end neural networks for subvocal for subvocal speech recognition”. They performed automatic speech recognition using an end-to-end neural network by extracting spectrogram features from EMG signal. Their baseline model had a three layered RNN using LSTM cells with a CTC loss function, with a hidden size of 256 for all three layers. To prevent exploding gradients, they used gradient clipping for gradient beyond a maximum norm of 10. Adam optimizer with a learning rate of 1e-3. For spelling mistakes in decoded utterances, they post-process the top-scoring decoded utterance for a given input with a second beam search step that aims to correct the utterance according to a language model. The decoded utterance gets split into tokens by blank character, and consider all character-level edits of each token that are an edit distance of two characters or fewer away, including inserting blank tokens. Then, the sequence of tokens that maximizes the probability of the utterance according to a four-gram Kneser-Ney language modelpre-trained on the TED-LIUM corpus was chosen. [24]

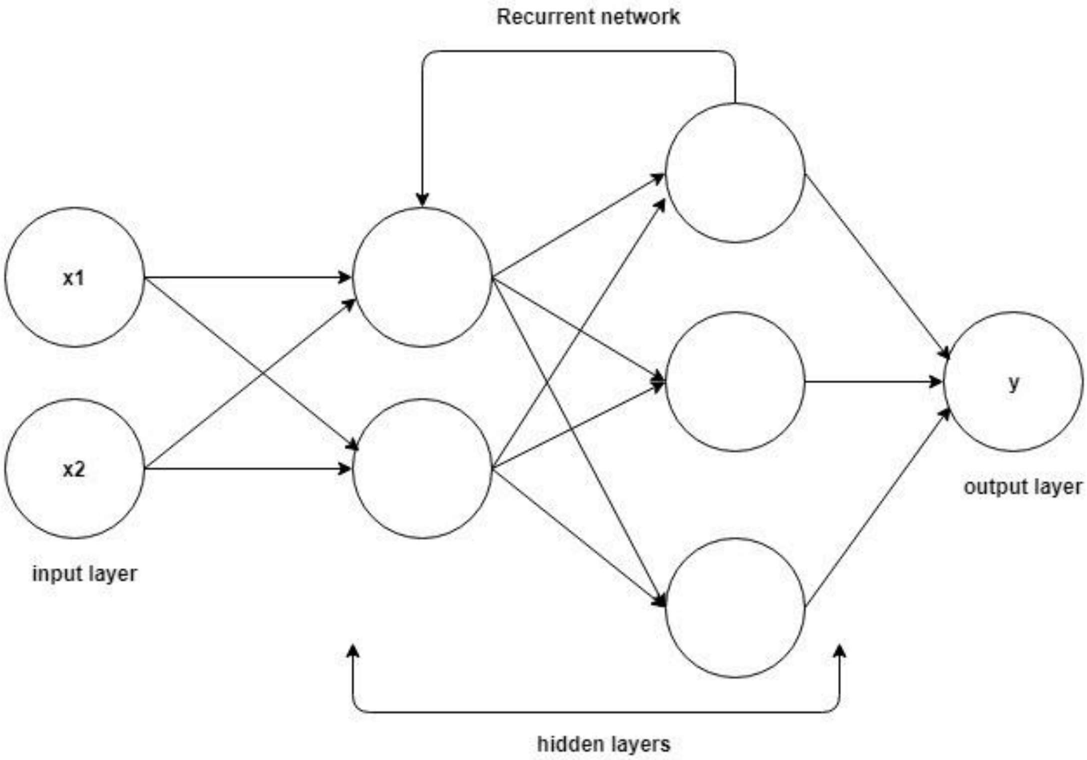

Figure 6-5: Architecture of Recursive Neural Network

7. RESULTS

So far, the development of circuit for EMG signal extraction and the analysis of the signal has been accomplished which was visualized using an oscilloscope. The circuit was first designed, simulated and analyzed using the Filter Designer tool of MatLab. The individual blocks of the circuit which includes amplifier, second order passive high-pass filter, second order active low-pass filter and notch filter were simulated and the results of the individual blocks were quite convincing.

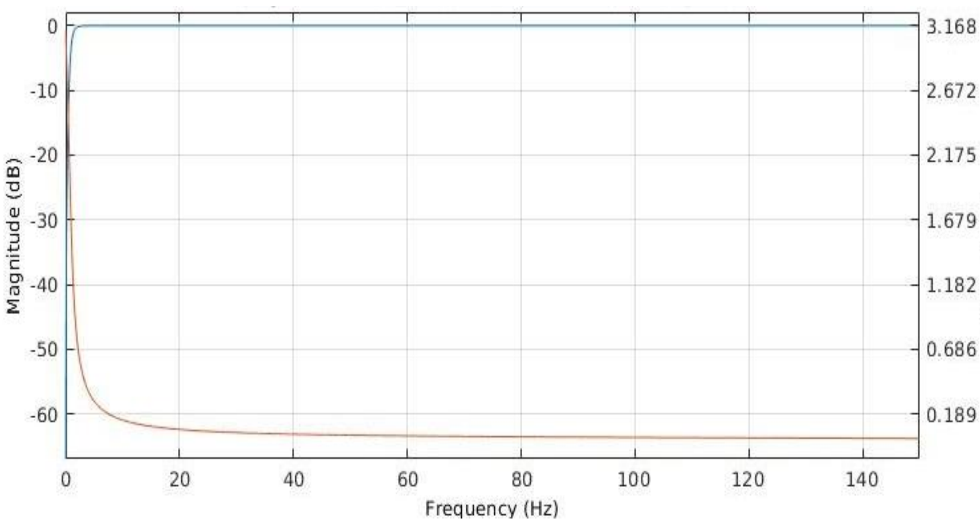

Figure 7-1: Magnitude and Phase plot of 2nd order Butterworth HPF with cutoff frequency at 1 Hz

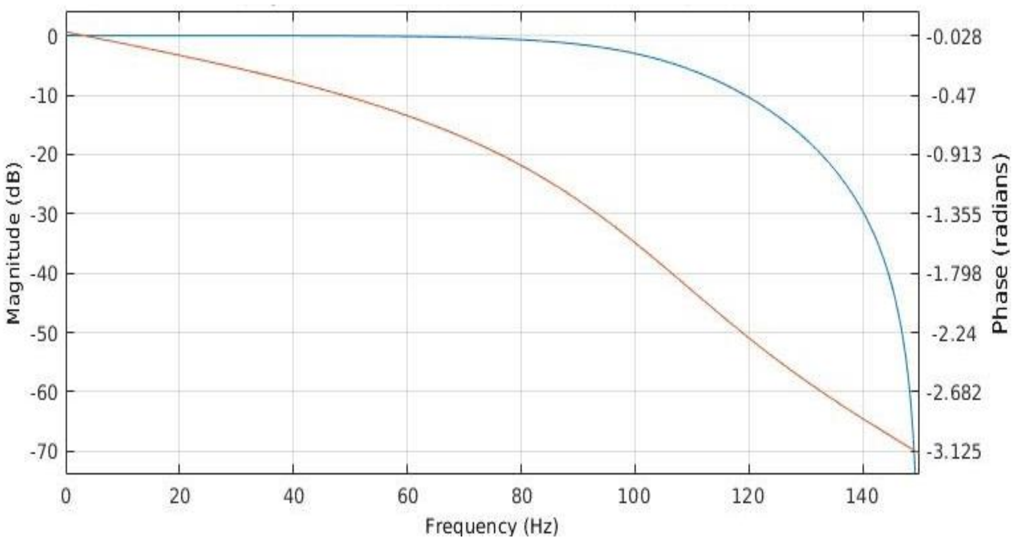

Figure 7-2: Magnitude and phase response of 2nd order Butterworth LPF with cut-off frequency at 100 Hz

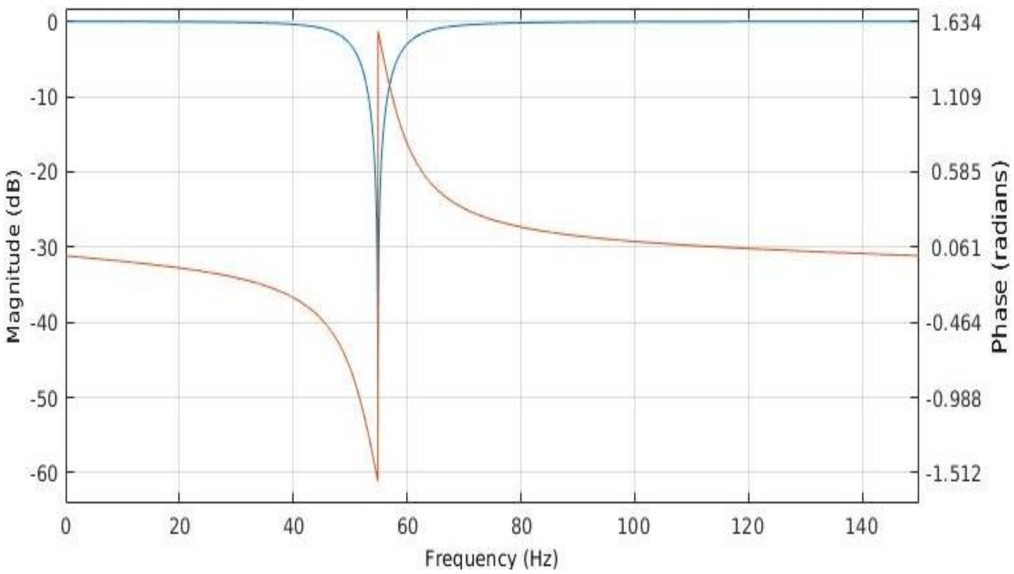

Figure 7-3: Magnitude and phase response of 2nd order notch filter of 50-60 Hz

After the simulation and analysis of the circuit it was designed in KiCad and then implemented into an actual practical circuit.

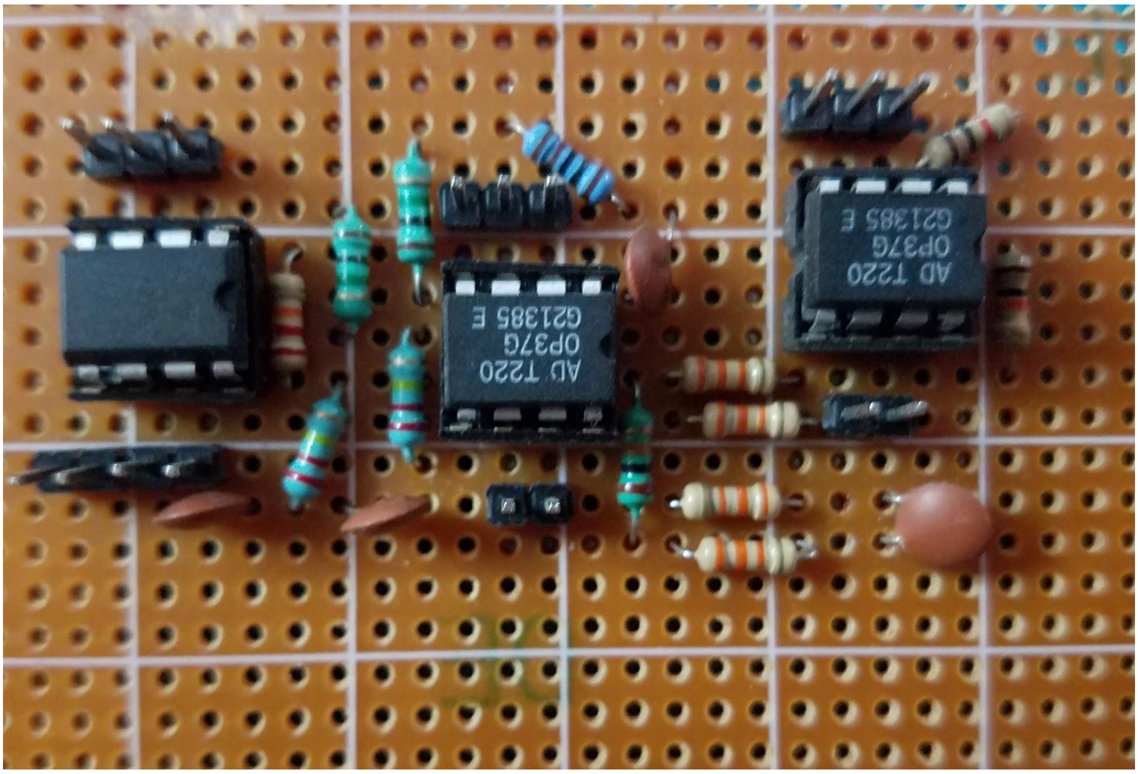

Figure 7-4: Designed circuit fabricated in matrix-board

The circuit was then tested initially by giving input of low frequency through frequency generator and the output was visualized in oscilloscope. The circuit was then tested by giving EMG input from the electrodes.

Figure 7-5: Initial setup for testing of circuit

As seen in the figure below spikes in the signal were obtained during the motion of the electrode attached part of the body while no spikes were seen when the body part was stationary.

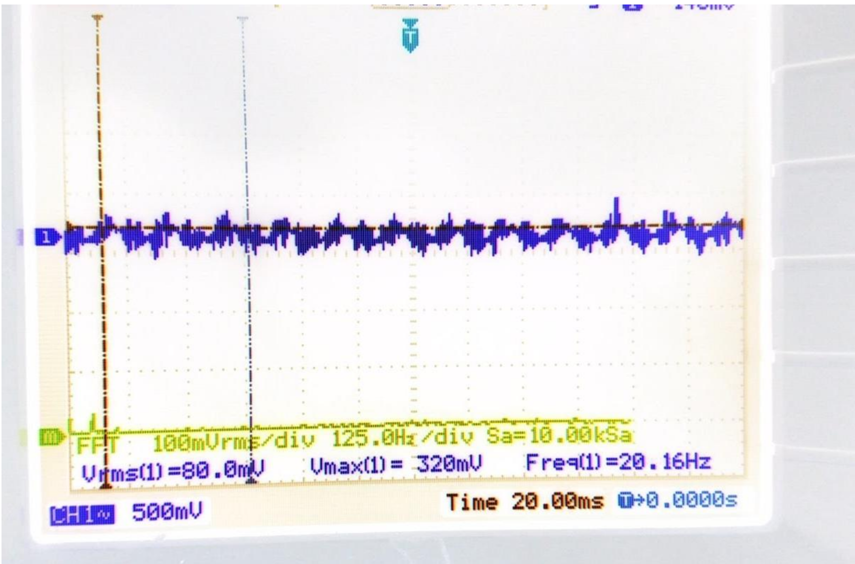

Figure 7-6: Signal when the electrode-attached muscles were at rest

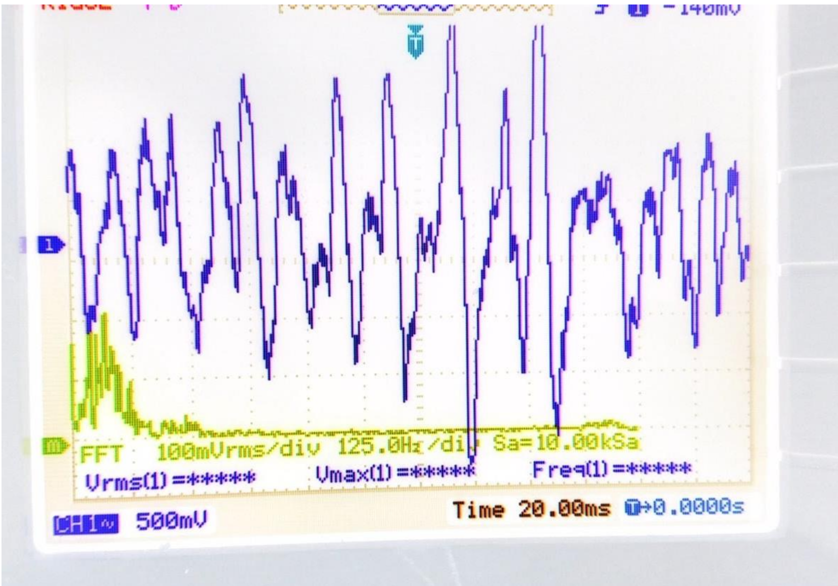

Figure 7-7: Signal when electrode-attached muscles were moved

8. ANALYSIS AND DISCUSSION

Due to limitations in different parameters and devices the output was not obtained as ideal expectation rather some magnitude shift, phase shift along with noise were found in the output signal. During the design of amplifier and filter circuits the non-significant values beyond the decimal place were neglected and the resistor value as calculated were unavailable in the market. Moreover the tolerance of the passive elements like resistor and capacitor were not taken into account during the calculation and design of the circuit. The effect of such neglected parameters were later found while analyzing the circuit in practice. The amplification factor of the amplifiers was attenuated due to which the output signal was attenuated by some factor. Similarly, the roll-off factor of the filters were not as calculated as a result of which transition band was extended and the noises from the frequency bands which were expected to be eliminated by the filter were introduced in the output signal. Also, magnitude as well as phase shifts were found due to imperfections in the filter and amplifier circuit.

The placement of the electrodes for signal and ground had a direct impact on the magnitude and frequency of signal generated. Only a slight displacement in the electrode position affected the output signal by a large factor. Another major factor affecting the signal output was the attenuation introduced by the skin layer between electrode and the muscles.

9. ACCOMPLISHED AND REMAINING TASKS

S.N	Tasks Accomplished	Tasks Remaining
1.	Research on Sub-Vocal Recognition	Conversion of signal into digital format
2.	Analysis and calculation of circuit parameters	Extraction of Fourier coefficients using STFT
3.	Simulation of circuit for EMG signal detection from 1 Hz-100 Hz and its response analysis in MatLab	Transmission of coefficients data through wireless medium to the computer
4.	Design of the circuit in circuit board	Preparing training data set
5.	Testing of low frequency signals from frequency generator in oscilloscope using our circuit	Testing different machine learning algorithm for minimal error
6.	Testing of EMG signals from Ag-AgCl electrodes in our circuit and visualizing in oscilloscope	Conversion of output data of neural network into text format

10. APPENDICES

10.1 Project Budget

Table 10-1: Budget of Purchased Items

S.N.	Title		Model	Quantity (pcs)	Rate (NRs.)	Price (NRs.)
3	Ag-AgCl Electrode		ECG EMG	50	10/-	500/-
4	Instrumentation amplifier		AD620	5	114/-	570/-
5	Op-amp		OP37AJ	10	114/-	1140/-
6	Passive electronic components	• Resistors • Capacitors • Header pins • Diodes	-	-	-	2000/-
8	Electrolyte		AgCl	250ml	50/-	50/-
	Total					4,260/-

Table 10-2: Expected Budget for items to be purchased

S.N.	Title	Model	Quantity (pcs)	Rate (NRs.)	Price (NRs.)
1	Arduino	Uno	2	950/-	1900/-
2	Bluetooth Module	HC-05	2	790/-	1580/-
3	PCB board	single sided	2	250/-	500/-
4	Shielded Cable	RCA	8 (1 m)	115/-	920/-
5	Miscellaneous	-	-	-	5000/-
	Total				9900/-

10.2 Project Timeline for part-A

Table 10-3: Gantt chart

Title	15-Nov	15-Dec	15-Jan	15-Feb	15-Mar
Brainstroming and title selection	30 days				
Component Selection		30 days			
Hardware model design		60 days			
Hardware testing			60 days		
System testing and debugging					30 days
Research	150 days				
Data Collection				60 days	
Documentation		120 days			

10.3 Circuit Diagram

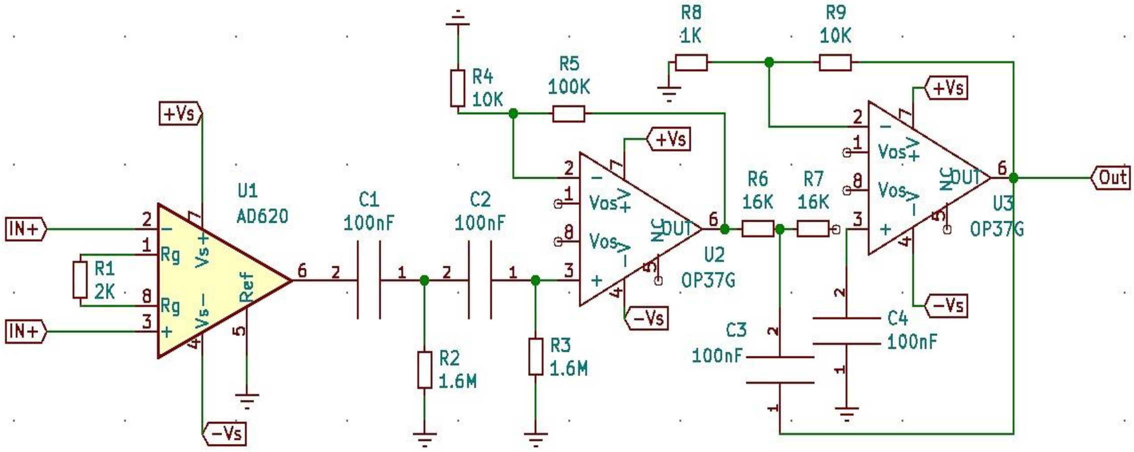

Figure 10-1: Schematic of designed circuit for EMG signal extraction

10.4 Module Specifications

Table 10-4: Specifications of instrumentation amplifier AD620

S.N.	Parameters	Specifications
1.	Gain Range	1-10,000
2.	Power Supply Range	±2.3 V to ±18 V
3.	Max. Supply current	1.3 mA
4.	Input Voltage Noise	0.28 μV p-p (0.1 Hz to 10 Hz)
5.	Bandwidth	120 KHz (G=100)
6.	CMRR	100 dB min (G=10)

Table 10-5: Specifications of amplifier OP37G

S.N	Parameters	Specifications
1.	Open-Loop Gain	1.8 Million
2.	Max. Supply Voltage	22 V
3.	Max. Supply Current	25 mA
4.	Bandwidth	63 MHz (Common Voltage @ 11V)
5.	Input Voltage Noise	80 nV p-p (0.1 Hz to10 Hz)

Table 10-6: Specifications of ADC of Arduino Uno

S.N	Parameters	Specifications
1.	Type	Successive Approximation Register
2.	Resolution	10 Bit
3.	Absolute Accuracy	±2 LSB
4.	Conversion Time	13 - 260µs

10.5 Relevant Datasets

Dataset for our project is referenced from a paper “EMG-UKA Trial Corpus” written by Michael Wand, Matthias Janke and Tanja Achultz. [Reference] It has datasets for silent speech for 1:52 hours by four speakers. The dataset is a 16-bit digital converted value. The whole dataset is taken with a 6-channel EMG signal, taken from muscles activated during silent speech. Muscles activated during the articulation are Levator Anguli Oris, Zygomatics Major, Platysma, Depressor Anguli Oris, Anterior Belly of Digastric and Tongue.

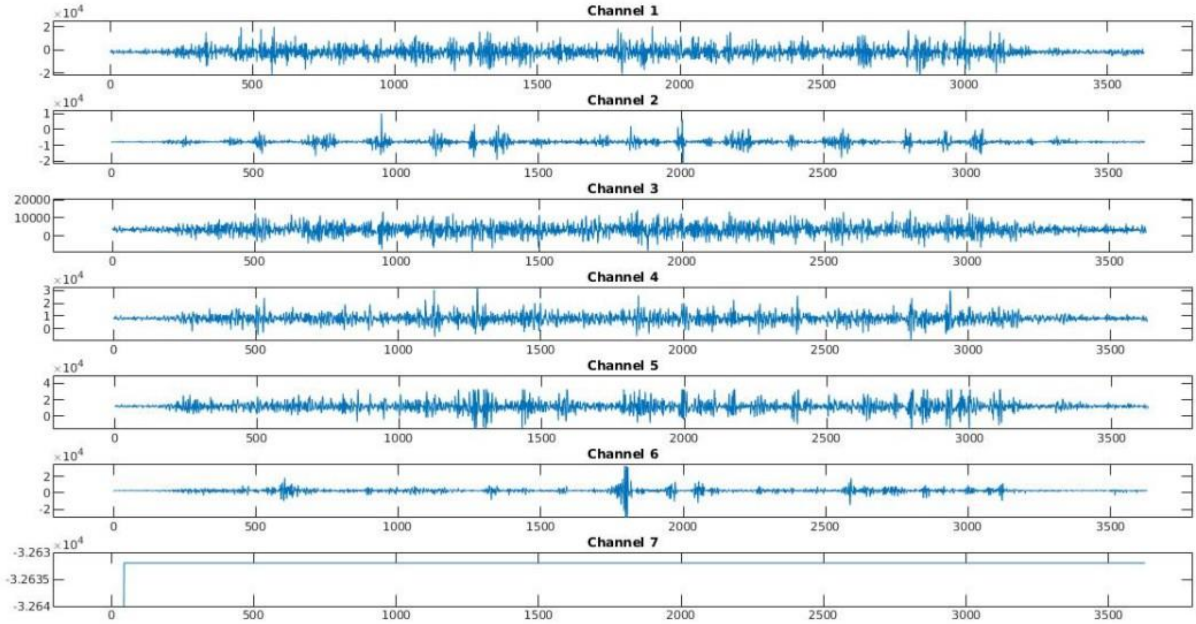

Figure 10-2: EMG signals from raw data obtained from dataset

Above figure shows EMG signals obtained from the dataset during citation of the sentence “THIS COUNTRY HAS RELIED ON IMMIGRANTS AND IS FOUNDED UPON A PRINCIPLE OF WELCOMING IMMIGRANTS” by a speaker. Figure shows signals of six different channels and channel 7 is a marker signal that is used to distinguish between two utterances.

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