TALLINN UNIVERSITY OF TECHNOLOGY

Faculty of Information Technology

Thomas Johann Seebeck Department of Electronics

IEEE70LT

Ojasvi Verma a121852

EMG ANALYSIS OF FACIAL ACTIVITY INTENSITY

Master thesis

Supervisor: Olev Märtens,

PhD,

Lead researcher

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Author’s declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

Author: Ojasvi Verma

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Abstract

A number of studies have been done about pain in infants, neonates and ICU (intensive care unit) patients. It is noticed from the earlier studies that severity of illness may affect the way infants and neonates express pain. Present pain assessment tools rely on behavioral and physiological measures which may not accurately reflect pain experience. If the infants, neonates cannot tell us verbally when he/ she suffers from a pain than facial expressions is one of the most natural ways of non verbal communication. At the moment, there are different techniques to read facial expressions for clinical purposes. Facial Action Coding System (FACS) is one famous technique to measure facial activity which is based on all the movements that human anatomy allows. EMG recording of the facial muscles is one of the most natural ways of non-verbal communication. Facial EMG Muscles recording is one of them that are hardly or not at all studied at the present.

The goal of my study has been to gather Facial EMG Muscle electrical signals as offline data, to analyze it. The Facial muscles, being responsible for raising the eyebrows and raising the mouth corners are measured simultaneously with the EMG during experiments. Detection and analyzes means in the work detecting the facial emotions of the person and analyze this data, how it is different from its normal face.

To gather the data, an experiment was carried out in our lab with my project colleague who had performed facial expressions, while data was recorded from bio patch. The experiment that had to perform in two facial muscles i.e. Frontalis and Zygomaticus. The Bio- electric SoC is used by to detect the bio- electric signals. It is a mixed single chip consisting of an analog front end (AFE), a successive approximation register analog to digital converter (ADC) and a digital core. The important aspect of the bio- electric SoC is that EOG, EMG, ECG and EEG signals can be successfully recorded through this.

Finally, the successfully recorded data is evaluated and analyzed by me in MATLAB environment by signal processing tools and methods. An algorithm for a signal processing of raw EMG signals to be converted into the signals that represent the intensity of facial movements has been developed.

This thesis is written in English language and is 46 pages long, including 5 chapters, 22 figures, 3 tables and 3 appendixes.

Annotatsioon

Näotegevuse intensiivsuse EMG analüüs

Mitmed uuringud on püüdnud selgusele jõuda, mil moel valu mõjutab imikuid, vastsündinuid ja intensiivraviosakonna patsiente. On täheldatud, et haiguse ägedus/tõsidus võib mõjutada, kuidas imikud ja vastsündinud valu väljendavad. Olemasolevad vahendid valu määramiseks tuginevad käitumuslikele ja psühholoogilistele meetmetele, mis ei pruugi niivõrd täpselt valu kogemist peegeldada. Kui patsient kannatab valu käes, ei ole tal võimalik seda verbaalselt väljendada, siis on just näoilmete kasutamine üheks loomulikumaks mitteverbaalseks suhtlusvahendiks. Kliinilistel eesmärkidel erinevate näoilmete vaatlemiseks on hetkel käibel mitmed tehnikad. Näoväljenduste kodeerimise süsteem (FACS), mis põhineb inimanatoomia plastikal, on üks tuntumaid meetmeid näoväljenduste mõõtmiseks. Näolihaste registreerimine EMG (elektromüograafia) abil aitab väljendada ühte loomulikumat mitteverbaalse suhtlemise moodust. Näolihaste EMG kasutamist on paraku vähe uuritud. Antud tõsiasi motiveeris teema valikul. Uurimise eesmärgiks on koguda näolihaste EMG andmeid, mida kasutasin ning analüüsisin. Uurimise all on näolihaste tekitatud elektrilised signaalid. Katsete käigus mõõdetakse EMG abil simultaanselt näolihaseid, mille abil tõusevad kulmud ning suunurgad.

Andmete kogumiseks viisime läbi katsed minu kolleegi abiga, kelle näoilmeid me registreerisime. Eksperiment teostati keskendudes kahele näolihasele - *frontalis* (otsmikulihas) ja *zygomaticus* (sarnalihas). Kasutasin bioelektrilist SoC-d vastavate signaalide tuvastamiseks. See on monokiip, mis koonseb analoogosast (AFE) ja analoog-digitaalmuundurist (ADC), et registreerida järjestikuseid samasusi, ja digitaaltuumast. Oluline aspect on et EOG, EMG, ECG ja EEG signaalid talletatakse edukalt bioelektrilise SoC abil.

Lõpetuseks hindan ja analüüsin salvestatud andmed Matlab'i keskkonnas, et sooritada saadud informatsiooni signaaltöötlus. Oma uurimuses kavandasin algoritmi, mis töötleb ümber toored EMG signaalid signaalideks, mis väljendavad näolihaste tegevuse intensiivsust.

Lõputöö on kirjutatud inglise keeles ning sisaldab teksti 47 leheküljel, 5 peatükki, 22 joonist ja 3 tabelit ning lisaks 3 Lisa.

List of Acronyms

ADC	Analog to Digital Converter
AFE	Analog Front End
API	Application Program Interference
AU	Action Unit
CHEOPS	Children’s hospital of eastern Ontario pain scale
DAC	Digital to Analog Converter
DSP	Digital Signal Processing
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyography
EOG	Electrooculography
F.A.C.S	Facial Action Coding System
FFT	Fast Fourier Transform
I.C.U	Intensive Care Unit
LDA	Linear Discriminant Analysis
LPF	Low Pass Filter
MATLAB	Matrix Laboratory
OSBD	Observation scale behavioral scale
NCFS	Neonatal Facial Coding System
PBCL	Procedure behavior checklist
PBRS	Procedure behavioral rating scale
PCA	Principal Component Analysis
PPPM	Parents postoperative pain Management
RMS	Root Mean Square
SoC	System on Chip

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Acknowledgements

I would like to express our deepest gratitude towards our deepest gratitude towards to my supervisor Lead Researcher Mr. Olev Märtens for providing sufficient guidelines and valuable scientific comments during the thesis work. His incredible support, inspiration and friendly behavior have helped me a lot to improve ourselves and the quality of the thesis documentation. Studying with him and in his laboratory was a great experience for me. I would also want to thank Mr. Amir- Mohammad Rahmani and Professor Johan Lilius for being my Co-advisor.

I would also like to thank my friends for all the support and motivation through my Erasmus Period, helping me to overcome the difficulties. Also I would like to express my special thanks to Anurag Thakur for his invaluable help in getting the offline EMG signal. Experiences and suggestions that we have shared with me will always be appreciated during my professional life.

Finally, I want to thank my family members for their never ending love and support.

Ojasvi Verma

Chapter 1

1. Introduction

The facial activity of a human can be a source of a vast amount of information [1, 3]. The face is the most significant part in the body surface. The face provides us an interface for us to an exchange the information, ideas with real world. On the face, all of the organs could use to sense or present the desired message and information. For example the ears can pick the sound, the eyes can obtain the picture of surroundings, the noise can smell, the skin has the sense of feel/ touch and finally the tongue tastes the food savour [2]. In the similar manner, a Facial muscle of our human face plays an important role in our social and emotional lives. Facial Muscles are visually observable, conversational and interactive signals that clarify our existing focus of attention and control our interactions with the surroundings and other persons in our surrounding areas. Healthy persons during every day life automatically recognize affective facial expressions quite well. Affective facial expressions can be quantitatively analyzed by skilled experts coding elementary facial actions. Another technique is to recording the electromyography signals of specific facial muscles like Frontalis muscle, corrugator muscle, zygomaticus muscle etc [3]. Both methods have their own advantages and disadvantages. In my Thesis/ research work, I will present a signal processing of Facial EMG signals.

The expressions of facial expressions and in particular the expressions of emotion are critical to everyday social life. Specific expressions have been including those of fear, anger, cheerfulness, sadness, nervous and disgust [4]. But one very important type of facial expression that has not been studied/ rsearch so much is the facial expressions of **Pain,** which can been used in applications like medical systems, psychological research, academic studies etc. Pain is one of the most common symptoms in critically ill patients and it is experienced by each patient in a distinctive manner. It is a subjective experience and to measure it in an objective way is hard [5]. In recent years, the questions of long-term behavioral effects of pain in patients and infant have generally attracted the awareness of human professionals. The need of for prevention and management of pain in patients and infants have gained worldwide acceptance. Different pain assessment methods have been developed, primarily focus on facial expressions of pain [6]. One method is to measure facial activity of muscles i.e. Electromyography (EMG) that measures the electrical activities of the muscles and the intensity of the activity. Another alternative method is to measure facial activity consists of vision based methods. The comprehensive one is facial Action Coding System (FACS) that describes facial activities based on all movements of the human anatomy allows [1]. But there is also another method to measure pain through video sequences and this method is based on LDA classifier [6, 7]. My thesis work focus on Facial EMG Activity intensity.

The most common bioelectrical signals measured in clinical practice or for study/ research purposes are Electrocardiography (ECG), Electromyography (EMG), Electroencephalography (EEG) and Electrooculography (EOG) signals. These signals are bioelectrical signals generate by the activity of the heart, muscles, brain and eyes respectively showing the characteristics of a dedicated physical or mental activity. When we record and monitor these bio-signals, it is used in a large number of applications such as heart disease diagnosis, muscle activation analysis etc [8].

Measurement of facial expressions is an important for research and assessment psychiatry, neurology and experimental psychology.

Consistent with the worldwide population trend, many countries are facing the problems of aging [8]. Chronic diseases are becoming the major causes of the death. According to US National Center for Health Statics, major chronic diseases such as heart disease, cerebrovascular disease and diabetes's account for 35.6 % of death in US in the year 2005 [9, 8]. In a research shows that of the nearly 5 million patients are admitted to the ICU every year, a likely 71 % of the patients remember experiencing pain during their stay in ICU [10]. The occurrence of chronic disease expected increases the total costs on healthcare and poses a grim challenge to the current health care system globally. Healthcare and well being services are usually offered within hospitals or medical centers. Citizens with chronic diseases as well as the people in post- surgery state need continuous monitoring of their health condition, as well as their families need to collaborate of their health condition especially the vital signs until their physical condition status become stable [8].

1.1. Task

The goal of my Thesis is to demonstrate the technique of Facial EMG for the purpose of clinical purpose. Because the human face may be considered as the richest source of information for revealing some ones emotional state (such as pain, anger, sadness etc) [2]. One question arises here that, (What is Facial EMG?). Facial EMG studies typically focus on the facial muscle activities. **The present study investigated the possibilities to acquire and process the facial EMG signals to extract the time- domain signal intensity (by various filtering, rectification and similar techniques), for further measuring the sensitivity of the signals to the effect of pain.** Facial EMG activity of the the zygomatic muscle (which controls smiling) and frontalis muscles were recorded and processing and analyzing possibilities investigated. The main advantages of using Facial EMG i.e. the patients in Intensive Care Unit, children and Neonates cannot experience their pain/ hurt verbally. Pain in new born bay is often unidentified because they cannot communicate with us [7]. Another important point is that we cannot observe the patients in ICU for a longer period time [11]. Another important point i.e. the major hurdle to analyze that actually how much pain young children and infants are feeling [25]. Facial expression is one of the assessment tools which will describe the Emotional pain intensity in neonates and patients in ICU. New applications also includes using facial EMG to measure emotional response while playing video games, human computer interaction but our main research focus is for the purpose of clinical purpose [11].

1.2. Facial expressions

In our daily life, the face is an object of major importance. Faces tell us the identity of the people. We are looking at them, analysis and provide information on gender, age and his behavior, among many others. Facial expressions occur from motion, pain or positions of facial muscles are known for some time to communicate emotions [12]. They are visually observable, conversational and interactive signals that clarify our current focus of attention and regulate our connections with the environment and other persons in our neighborhood. Facial emotion plays an active role in humans because they often tell us how people feel. Facial expressions also form an important part of verbal communication between humans [12]. Darwin concluded that facial expressions are the same for everyone, only differences in their cultural difference [13, 14].

There are many different types of facial expressions, some express basic emotions. Ekman even describes all emotions as basic like happiness, sadness, fear, surprise, anger while other facial expressions are purely used for non- verbal communication like nervousness or are simply the result of an action [12]. For example, the eyes are viewed as significant feature of facial expressions. Eyes are the organ of vision, instead of this blinking rate can be used to indicate whether a person is nervous or not. Also contact of eye is considered an important aspect of interpersonal communication. In next section I discuss about the famous and important methods to analyze facial expressions.

1.2.1. Facial Action Coding System (FACS)

The facial action coding system (FACS) (it is developed by Ekman and Friesen, 1978 [12]) is the most usually used technique/ method for coding the facial expressions in the behavioral sciences [15, 16]. It is a study/ research tool useful for measuring any facial expression that a human being can make [17]. This method describes facial expressions in terms of 46 component movements which approximately correspond to the individual facial muscle movements. An example is shown in figure 1 [15, 16]. It provides an objective and comprehensive way to investigate expressions into elementary components, analogous to decomposition of speech into phonemes i.e. it is complete and it has proven useful for discovering facial movements that are indicative of cognitive and emotional states [16]. The primary drawback to the use of FACS is that it requires lot of time required to code. It was developed for coding by hand, by using human experts. It takes over 100 hours of training to become proficient in FACS and also it takes approximately 2 hours for human experts to code each minute of video.

Facial Action Coding System (FACS) used to describe any possible facial expressions and exit of Action units (AU) that represent the small action segments in the building of facial expression. FACS AU s is likely depended on what the facial muscles allows the face to do [13]. Action Unit (AU) is an independent of interpretation and smaller actions cannot be described by originates of actions [12]. An overview of Action units (AU) and FACS with underlying facial muscles can be found in Appendix A [18].

It is at present used as a research/ investigate tool in a number of branches of behavioral science and a major disadvantage to this method is the time required to train human expert and to manually score the video tape. Automating the Facial Action Coding

System would make it more widely accessible as an investigate/ research tool and it would provide a good foundation for human- computer interaction tools.

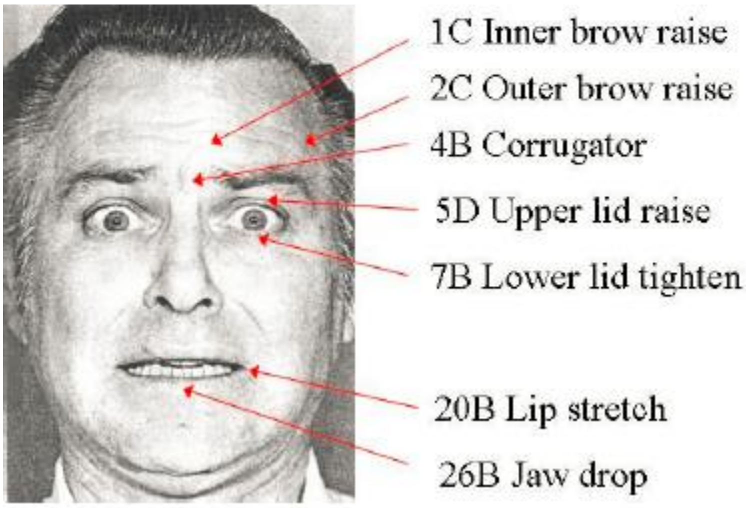

Figure 1. Example of facial action from the FACS [15].

1.3. Electromyography

EMG stands for Electromyography. EMG research benefited considerably from latest developments in detection and computing technology. To measure facial activities of human being, another method is Electromyography (EMG). It measures/ records the electrical activity of the facial muscles and the intensity of the activity [1]. EMG is a scientifically technique concerned with the development, recording, investigate and analysis of myoelectric signals. In the state of muscle fiber, myoelectric signals are formed by physiological variations [19]. EMG has a high temporal resolution which makes it better for the measurement of spontaneous activity that has a rapid onset and duration. Figure 2 shows an electromyography signal [19]. The advantage of this method i.e. EMG signals are simple and easy to record and understand. It is sure that we can get/ detect facial activity, when it is not visible by naked eye [21].

Facial Electromyography (FEMG) is an emerging as a more precise and sensitive technique to measure and record changes in facial expressions than visual observation. EMG measures muscle activity by detecting and amplifying the small electrical impulses that are generated by muscle fibers when they contract. It measures minute changes in the electrical activities of facial muscles which reflects minute muscle movements. This method has been shown to be capable of measuring the facial muscle activity to even weakly evocative emotional stimuli [20].

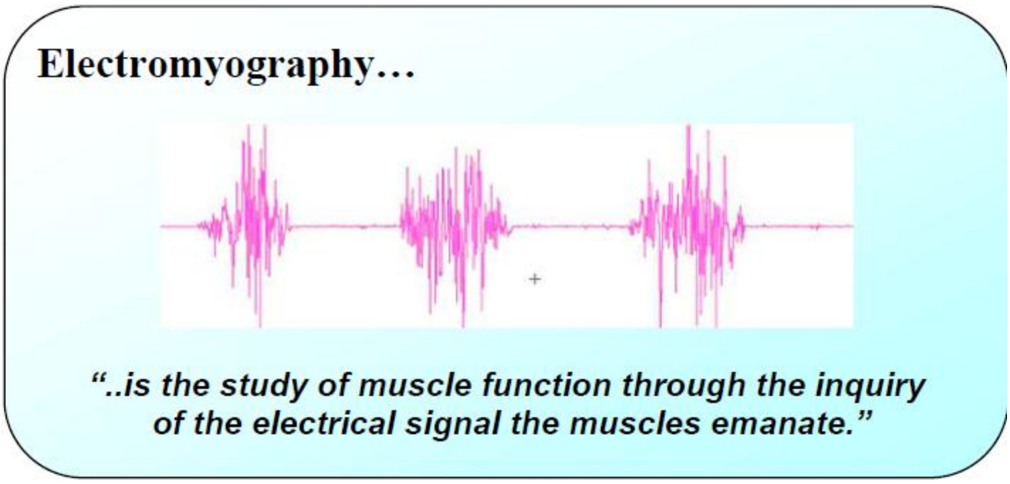

Figure 2. Electromyography signals [19].

1.3.1. Use and Benefits of Facial EMG

The human facial activity can be a source of vast information [1]. The measuring the facial electromyography will get much more useful information. Some potential applications performed by facial EMG is that the cerebration information including emotion, pain, mentally disorder, fatigue etc could leak out from face. For the paralytic, who is resulted from the accident or illness, the facial muscle could be the last failed motor unit. It can play a dominant role in clinical diagnosis and biomedical applications [2]. Typical benefits of Facial EMG are:-

- It is a precise and sensitive procedure to measure emotional expression.
- It is able to measure or detect weak facial muscle signals.
- It is less intrusive than other physiological measures like Electroencephalography (EEG) and f MRI.
- Facial EMG measurement technique is often the only useful approach when movement is not visible by naked eye.
- It does not depend on languages and does not require memory.

1.3.2. Recording & Analysis of EMG Signal

A general technique used to record the EMG signal can be subdivided into three stages:

(1) Electrode selection and placement

(2) EMG Recording

(3) Signal Processing.

In Facial EMG every step should be carefully handled, so that it is easy to eliminate noise and to correct measurement error. In my Master Thesis, I contribute my work on signal processing stage and it shows my results in Chapter 4.

- Electrode Selection and placement: - Electrode selection and procedure is a first step. Bio potential or the current in the human body which can be picked by the electrode between the human body and measurement instrument. It is basically a transducer which can convert one form of energy into another form. In this it take bio potential signal from our body convert these signals into electrical signal. Two types of electrodes that are commonly used for detecting EMG Signals i.e. surface and needle electrode, where the surface electrode is mostly used because it is non-invasive. The comparison between the electrodes is mentioned in table 1. below [2].

Table 1. The comparison between surface and needle Electrode [2].

	Surface Electrode	Needle Electrode
Advantages	1. It is Easy to use. 2. Surface electrodes are Non- invasive. 3. It has large recording region. 4. These electrodes are safer. 5. No hider movement.	1. Electrodes are Capable of detecting MUAP. 2. Needle electrodes have better selectivity. 3. High signal to noise ratio.
Disadvantages	1. It can measure only the surface muscle EMG. 2. It has low signal to noise ratio. 3. Surface Electrodes has poor selectivity. 4. Artifact.	1. It is difficult to use. 2. Invasive. 3. These electrodes are movement obstructing. 4. Needle Electrodes are hazardous.
Applications	1. The large muscles are recorded. 2. Violent exercise.	1. It can record single motor unit or small muscle. 2. It can record deep into muscle.

Surface electrodes are attached to the skin with double- stick adhesive collars. Surface Electrode detects the EMG signal through skin using a conductive paste or gel, which is most often used in a paired electrode configuration. The amplitude and spectrum of the signal will depend on the location/ position of the electrode. We need to put the electrode on the suitable position to get the exact Facial EMG. The best site of electrode is located at the midline of the muscle of the muscle stomach. Amplitude of Facial EMG signals is very low because finding the correct/ right position of electrode is not easy task/ job [22, 2]. Electrode location for measuring facial activity is shown in Figure 3 [22]. Relevant data are available for only two facial muscles.

The common reference electrode is also known as ground. The ground electrode is placed at the midline app 3-4 cm superior to the upper borders of the inner brows. In human, the frontalis muscle only serves for facial expressions and which covers parts of the skull. In frontalis, electrode is placed on imaginary vertical line 1cm lateral to the vertical line that traverses the pupil of the eye. On the other hand Zygomatic major is a muscle of facial expression which draws the angle of the mouth superiorly and smile. In Zygomatic major, one electrode is positioned midway along the an imaginary line joining the cheilion and the preauricular depression and the second electrode is placed 1 cm inferior and medial to the first (toward the mouth) along the same imaginary line [22, 3].

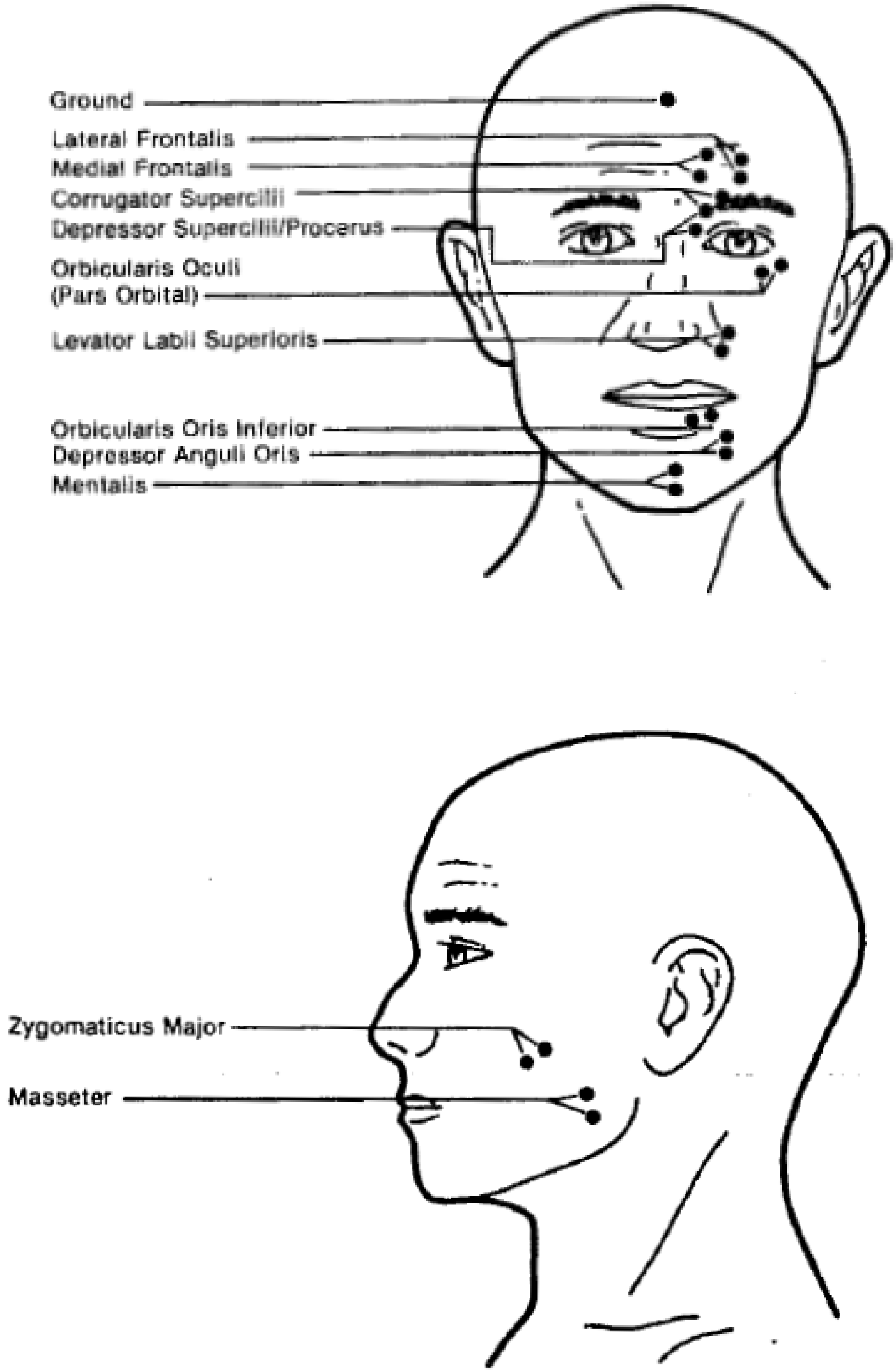

Figure3. Electrode locations for measuring Facial EMG activity [22].

- Signal Processing: - Signal processing stage is our second stage. The raw EMG recording contains very significant information and that I think may serve as a first objective information and documentation of the facial muscle innervations. Before measuring Facial EMG Signal, it should be kept in mind that EMG signals still contain the part of noise and error which is generated by other muscles of face, electrode contact or by power line interface [2, 23]. So a signal processing is necessary. In the first stage, we attach or insert the electrode on the patient skin, which is over Facial muscle. The collected EMG signal is delivered to the preamplifier. The preamplifier provides two functions:-

1. EMG signal intensity is too small that the computer could not read it.
2. The loading effects could be minimized by the high input impedance of an amplifier [2].

subsequent pre amplification, Analog to Digital converter, the predominated frequency range of Facial EMG signals the EMG signal must be band pass filtered (Butterworth filter) within the frequency range of 20-550 Hz [3]. It is also required to remove the 50 –Hz power line interference by applying a 50 HZ notch filter. It is nothing but it is a band stop filter (BSF). In signal processing, we use rectifier to convert all negative amplitude to positive amplitude, the negative spikes are “moved up” to positive or reflected by the baseline. In this we take the absolute value of the signal and it is known as full wave rectification. This step is essential for getting the shape or “envelope” of the EMG signals [1, 19, 41].

- EMG recording- : The EMG is recorded by using an electrode placed on the facial muscles. The bio-electrical activity measured by facial muscle electrode and the ground electrode are sent to an amplifier. The amplifier eliminates random voltages by electrical noise by subtracting the signal from the ground electrode from the muscle electrode and finally produce raw EMG signal [22].

1.4. EMG Analysis

The analysis of Facial muscle using EMG signals is performed with the frequency spectrum computed with Fast Fourier Transform (FFT). The EMG signals have frequencies near 20- 500 Hz, so typically the sampling frequency is used 1000 Hz [22]. An example of the time domain and frequency spectrum of facial EMG Signal achieved with this method is obtainable in Figure 4 [24].

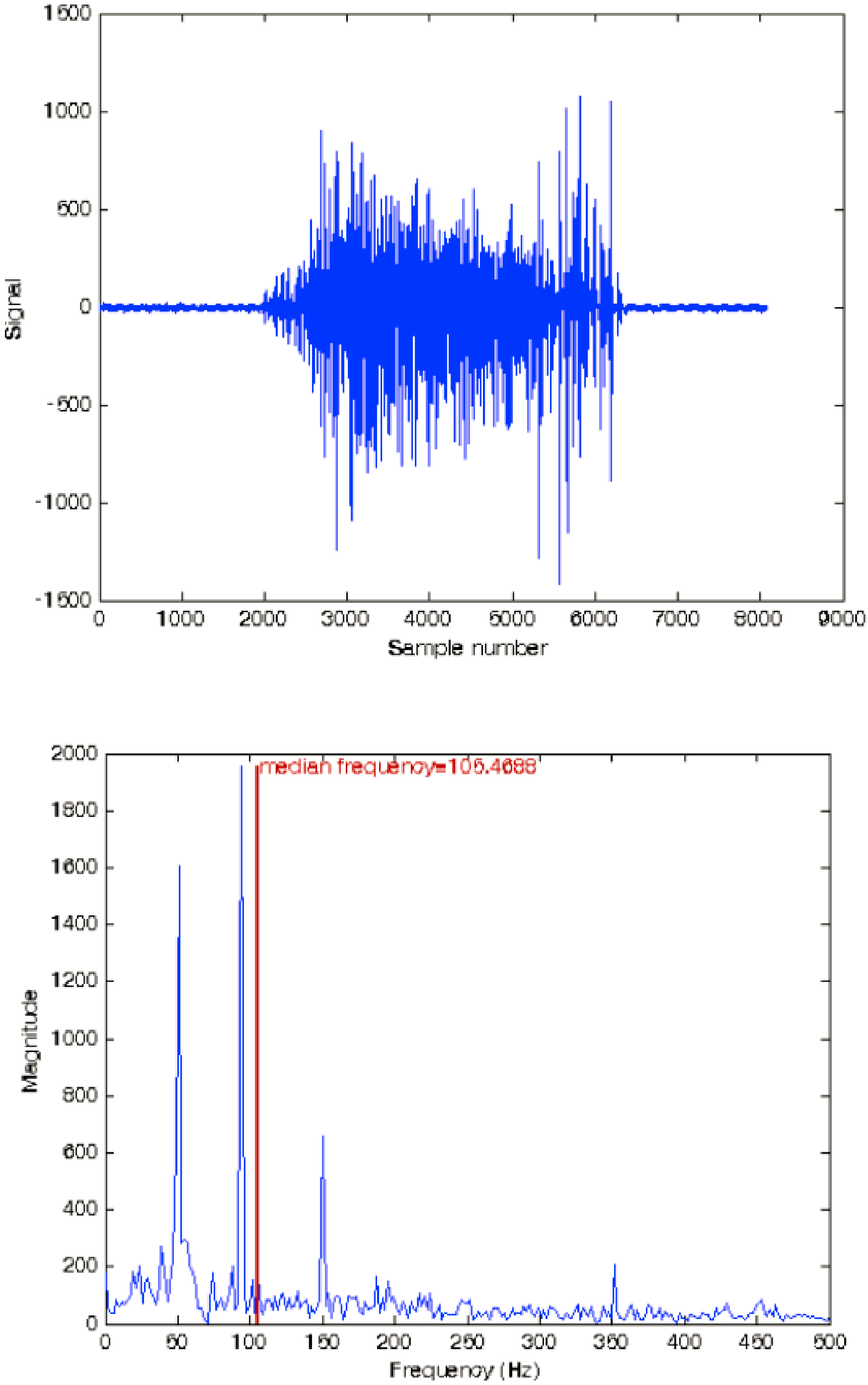

Figure 4. Time domain and Frequency spectrum of the EMG Signal [24].

The EMG signal is a complex one which is affected by the anatomical and physiological properties of the muscles under research/ study. Frequency spectrum of EMG signals must be obtained in order to examine the frequency domain activities and characterized the frequency components of EMG signals. For this motive Digital Signal Processing (DSP) methods should be beneficial because EMG signal be decomposed. Fast Fourier Transform (FFT) method was used to obtain the frequency spectrum of EMG signal.

Chapter 2

2. Overview of the field

In this chapter, the related work is discussed which was done before in this field. The work done by me in my Master Thesis and the related work done in past, make my work unique. In past no one has work on EMG measurement of Facial muscles activities who analyze the patients in ICU and neonates. In past, most of work done in human-computer interface, analysis of EMG signal (not so much work done in the field of Facial Muscles), designing of board and behavioral pain assessment. In the following section I am discussing about the past work done in this field.

2.1. Behavioral Pain Assessment

At present, the capacity of health care system is insufficient to treat all the patients face to face. When a patient suffers a pain, he/ she plays an important role in shaping individual feelings. Especially when the children whose age ranging from new born/ infant/ neonate to adolescent. Children and infants who cannot express their feeling themselves verbally. Behavioral assessment tool / scale are developed to understand, evaluate the level of pain and other variables for children/ infants. This assessment method is also useable for adult and old people but they can express their feeling themselves verbally. Behavioral assessment has designed different methods/ tool/ scales to assess pain for infants/ toddlers/ adolescents. These are PBRS (procedural behavioral rating scale), OSBD (observation scale behavioral scale), PBCL (procedure behavior checklist), FLACC (Face, legs, activity, Cry, Consolablity), PPPM (Parents Postoperative Pain Management), CHEOPS (Children s hospital of eastern Ontario Pain Scale) etc. Each method have their own characteristics like age, score ranging from, behavior code, time, burden, aspect of pain. An important issue in the field of behavioral assessment of pediatric pain as to whether some scales primarily measure pain and other primarily measure behavioral distress or whether pain and behavioral distress should be separated. The facial expression is one of the best behavioral indicators for pain assessment [25, 26, 27, 28].

2.2. Facial Expression Recognition of pain

In recent years, it s a big question of long term behavioral effects of recurring pain in patients has prevalently concerned the attention of health professionals. The need for prevention and management of pain in patients has gained universal attention. Various pain assessment tools / instruments based on facial expressions of pain have been developed. But pain assessment in a recently born person is considered one of the challenging jobs because neonate cannot verbalize their pain experience. Based on such research Grunau and Craig developed Neonatal Facial Coding System (NCFS) in 1987. The main drawback, the use of such assessment tools is the subjectivity of the observer.

The automatic recognition of facial expressions of pain has potential medical significance. In their work they try to tackle the trouble by applying modern facial expression recognition techniques to the task distinguishing pain expression from non-pain expressions. It is hard to understand, what is the actual position of neonate facial expression of calm or cry or pain [29].

In other research work, a newborn pain monitoring system is proposed and designed which automatically detects the condition of the newborn through continuously monitoring the newborn. It is based on the skin color that robust for different type of skin. Based on these facts, the facial are significant different from the normal condition until the pain condition can be detected. This system is very simple, fast and effective to alert the medical staff [30, 31]. The block diagram of the proposed system is shown in figure 5.

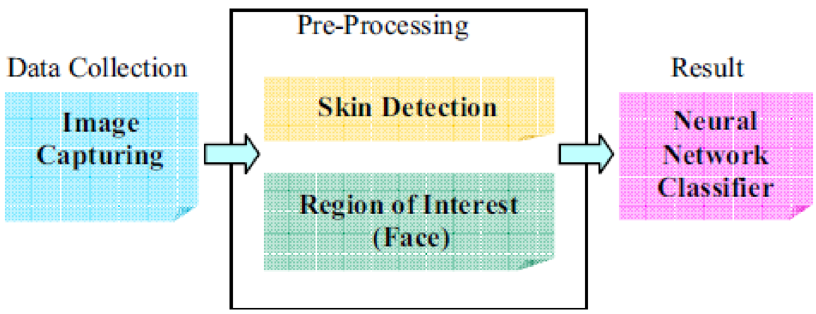

Figure 5. Block diagram of Pain detection [30].

In another research in the past, facial expressions of pain have been focus of behavioral. It was noticed that pain expressions, play an vital role in social communication like othe facial expressions. They present two systems for view based pain expression recognition through video analysis [32, 33, 31].

2.3. Automatically Infant Pain Recognition Based on LDA Classifier

According to their research work, an infant pain monitoring is designed from the method which is based on Haar Cascade classifier to detect the face. After capturing the image the skin color based algorithm is applied to detect the face in the images then eye and mouth portions of the image are separated from the face in the images then eye and mouth portions of the image are separated from the face. The condition of the image was determined based on a LDA classifier based on Principal component Analysis (PCA). The face detection algorithm scans an image and returns a set of locations that are believed to be faces the algorithm uses Ada- boost classifier that aggressively prunes the search space to quickly locate faces in the images. The paper presents the challenges and possibilities of infant pain automatic detection and analysis of infant faces. It shows the result, identification rate of reaches 93.12 % [5].

Principal Component Analysis (PCA) is a statistical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. PCA is a standard technique for dimensionality reduction and has been applies to a broad class of computer vision problems like features selection, object recognition and face recognition [5].

Linear Discriminant analysis (LDA) is a method used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events. It is used as linear classifier or more commonly for dimensionality reduction before later classification [5].

2.4. Design of digital filter for bio electric signal processing

In this work, the task have been to design efficient digital filters to eliminate noise/ unwanted sources associated with the bio electric signal so as to eliminate all the noise /unwanted sources associated with the bioelectric signal as output from the filters. I give main focus on bioelectric signal filtering where the signal retrieve from the electrodes of

EMG signals is interference with many noisy sources like power line interference, base line wander noise, motion artifact noise etc.

The noise introduced during the process of recording the EMG, EEG, ECG signals because of the low magnitude of many electric signals originating from the human body. The noise level determines the lowest perceivable amplitude in a bio potential recording. They had written in their work, that patient itself can be a source of noise. It also mentions the table which illustrates the amplitude and frequency bands of human physiological signal which is shown as table 2 [23].

In their work, they had developed a reconfigurable platform to record and refine the electrical activity of the heart. It includes designing of simulink model for filtering the bio signal in MATLAB environment. They gave main focus on designing the efficient filter designs for the removal of major noise sources in the EMG signal. Figure 6 and 7 shows the input bio signals (EMG signal) and the simulink result of design shows how, the noise free EMG signal looks like [23].

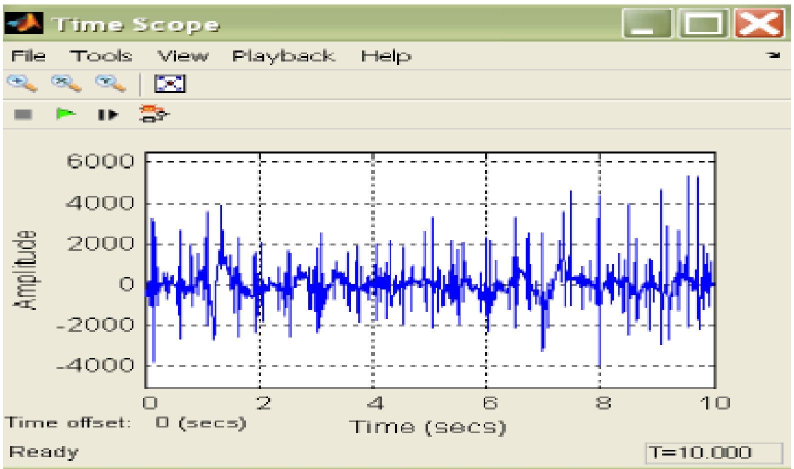

Figure 6 Input EMG Signal [23].

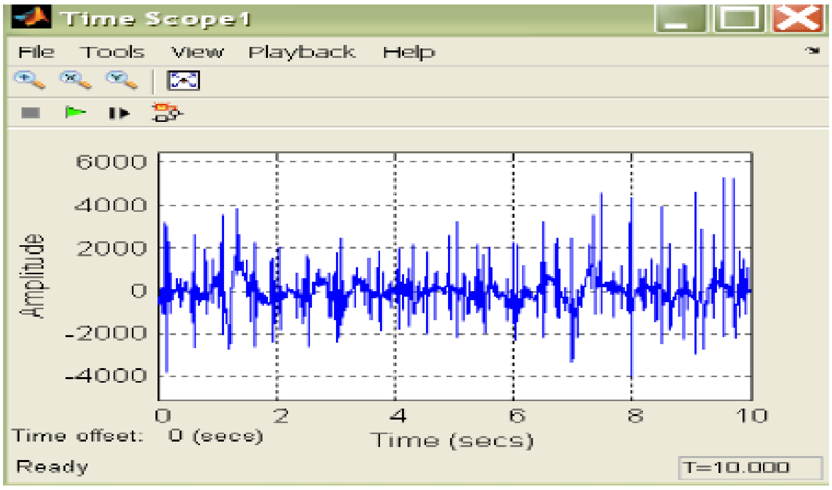

Figure 7. Simulation result shows noise free EMG Signal [23].

Table 2. Human physiological signals and their ranges [23, 8]

Parameter	Amplitude (mV)	Measurement range (mV)	Frequency range (Hz)	Measurement method
ECG	1-5	0.5- 4	0.01- 250	Skin electrodes
EEG	0.001-0.05	5- 300	DC- 150	Scalp electrodes
EMG	1-10	0.1-5	DC- 10000	Needle/ skin
EOG	0.4- 1	50-3500	DC-50	Contact electrodes

2.5. Design & implement hardware

This research work done by Mr. Geng Yang at KTH (Stockholm), they have designed and implemented a bioelectric System on chip. Electrocardiogram (ECG), electromyogram (EMG), Electroencephalogram (EEG) and Electrooculogram (EOG) signals are the most general bioelectric signals measured in clinical practices for study/ research activities. These are bioelectrical signals generated by the activity of the heart, Facial muscles, brain, muscles and eyes respectively showing the characteristics of dedicated physical or mental activity. The recording, analyzing and monitoring of these signals is used in different types of applications like heart disease diagnosis, muscle activation etc [8].

The designed low-power System on chip (SoC), which successfully records the four different bio electric signals including ECG, EMG, EEG, and EOG. The architecture of a designed System on chip is shown in Figure 8 [8]. The proposed chip is a mixed – signal chip which is divided into three parts:-

2.5.1. A digital core

First the author has designed the digital core, it is responsible for digital bio- signal acquisition, buffer and transmission. It also takes charge of communication between sensor nodes and the network management. The digital core is fabricated in a 1P6M 0.18 μm mixed mode CMOS technology occupying a total area of 1.5 mm * 1.55 mm [8, chapter 3].

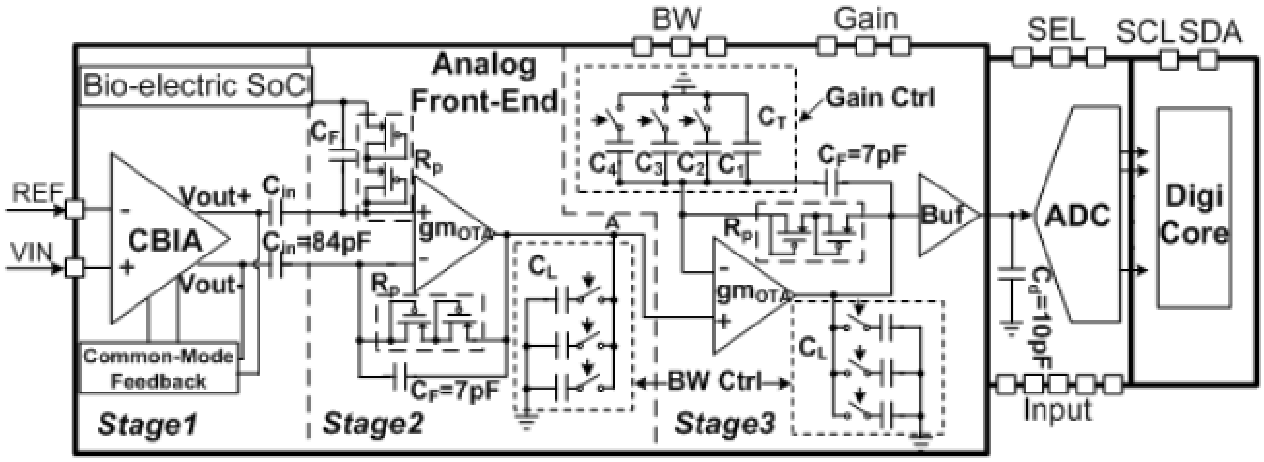

Figure 8. Architecture of bio electric SOC [8].

The main features of this digital core are following below:-

- Various interfaces: Analog to digital (ADC) interface (it is responsible for ADC control and digital data collection when the ADC output is ready), RAM interface, wireless interface (the considered bio signals are gathered on one ASIC and sent out via a wireless module) [8].
- On chip RAM which enables the digital core to buffer the digitized bio- signal.
- On chip implemented two- wire serial transmission protocol, including the frame structure for broadcast commands and unicast commands [8].

2.4.2. Analog Front End: Bio- electric signals display weak/ low amplitude signals and low frequencies. The circuit is required to complete the severe needs for the bio- signal detection: high input impedance, low power and low noise. These weak/ low signals from noisy surroundings are picked up by the Analog Front End (AFE) and amplify these signals and remove the noise/ unwanted signal from the desired bio electric signals [8, 42].

2.4.3. **Analog to Digital Converter (ADC):** The signal received by them i.e. bio electric is an analog signal and to analysis these we have to convert these signals into digital signal. A successive approximation register analog to digital converter (SAR ADC) which is used to convert the analog signal to digital signal. A standard 8-Bit charge redistribution SAR ADC input channel is implemented in a fully differential architecture [8, 42].

2.4.4. Results

The real bio-electrical signals are acquired by recording from the fabricated SoC, from healthy volunteers. The gain of 57 db with bandwidth from 17 Hz to 1.5 KHz is used for EMG measurement. For verifying the EMG measurement, the electrode pair is placed on the biceps of right arm. EMG signal is detected and recorded when the subject contract and relaxes his biceps. The measured four-second EMG signal is shown in Figure 9 and its Fast Fourier Transform (FFT) (as magnitude) of a selected signal segment. It shows that most of the frequency range from DC to 300 Hz and the dominant energy is in 10 Hz to 150 Hz. Chip has also verified for other bio-electrical signals ECG, EOG and EEG. But I am working on EMG signals. In current work attention has been about acquiring of EMG signals [8].

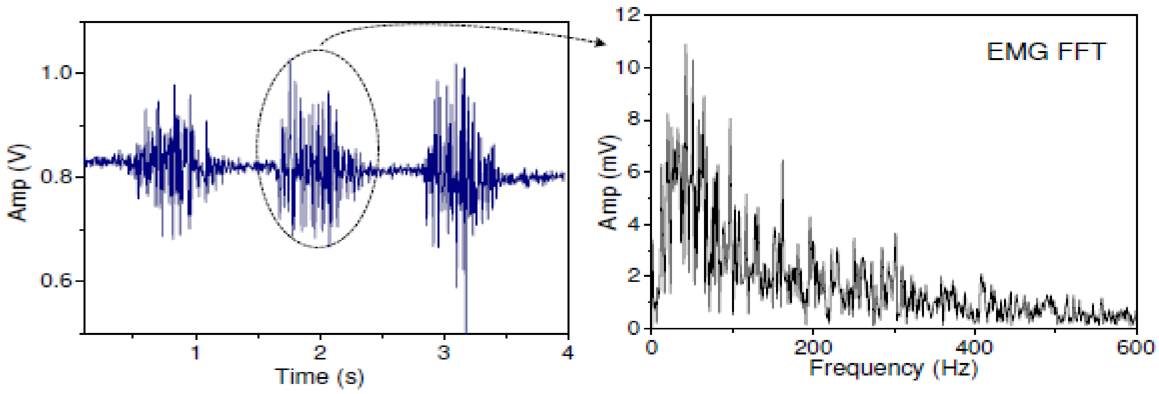

Figure 9. Measured EMG signal and it's FFT [8].

Chapter 3

3. Experimental part

This chapter presents the proposed methodology to analyze the EMG signal. An experiment was conducted to gather data of facial expressions recorded with an Electromyography (EMG) recording device. The data was analyzed with the focus on change of facial expression. This chapter describes the experiment design, the experiment procedure and the methodology of the analysis of the gather EMG data.

3.1. Experiment design

The goal of the experiment is to gather data of Facial muscles. Flowchart 3.1 shows the flow chart shows the procedure, which hardware or environments are used in the process of recording the Facial EMG signals to analysis these signals. Physiological EMG recording were performed in a university lab.

Facial Muscles

↓

Bioelectric SoC

↓

Arduino/ Panda board

↓

Matlab/ Simulink Environment

Flow chart 3.1 Experimental procedure.

3.2. Facial Muscles

During an experiment we consider the variables that affect EMG signal, a set of criteria was established to assist the choice of the Facial muscle where the validation measurements were going to be performed. Table 3.2 [3] shows a Facial action during the expressions of elementary emotions according to Ekman and Friesen.

Table 3. Facial actions during the expression of elementary emotions [3].

Elementary Emotions	**Muscles Involved**	**Produced Actions**

Happiness	• Orbicularis oculi • Zygomaticus major	Closing eyelids Pulling mouth Corners upward and laterally
Surprise	• Frontalis • Levator palpebrae superioris	Raising eyebrows Raising upper eyelid
Fear	• Frontalis • Corrugator supercilii • Levator palpebrae superioris	Raising eyebrows Lowering eyebrows Raising upper eyelid
Anger	• Corrugator supercilii • Levator palpebrae superioris • Orbicularis oculi	Lowering eyebrows Raising upper eyelid Closing eyelids
Sadness	• Frontalis • Corrugator supercilii • Depressor anguli oris	Raising eyebrows Lowering eyebrows Depressing lip corners
Disgust	• Levator labii superioris • Levator labii superioris alaeque nasi	Raising upper lip Raising upper lip and wrinkling nasal skin

3.3. Bioelectric SOC

This part is described in section 2.3.

3.4. Arduino Board

It is a single board microcomputer, intended to make the application of interactive objects or environments more accessible. The hardware of an Arduino board consists of an open source hardware board designed around a 8- bit Atmel AVR microcontroller or a 32 bit Atmel ARM. An important aspect of the Arduino is the standard way that connectors are exposed, allowing the CPU board to be connected to a variety of interchangeable add on modules known as shield [34, 35].

In my Master Theis, I use Arduino due board, its main use is it convert Analog signal into digital signal. It is a microcontroller board based on the Atmel ARM Cortex M3 CPU. It is a 32 bit ARM microcontroller. It has 54 digital input/ output pins, 12 analog inputs, 4 UARTs, a 84 MHz clock , two Digital to Analog (DAC), a JTAG header and an erase button. Figure 10 shows the view of an Arduino board [35].

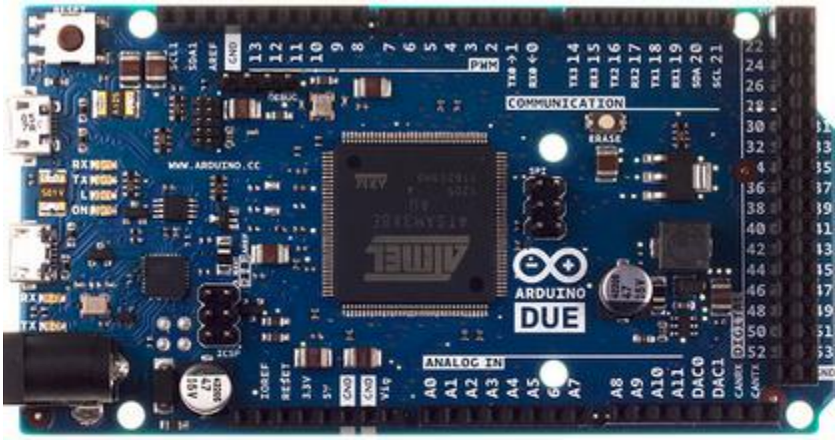

Figure 10. Arduino Due board [35].

Another main feature of Arduino Due board is that it is used for interferancing the MATLAB environment. The code used for connecting with a MATLAB is below.

```
Void setup()
{
// initialize serial communication at 9600 bits per second:
Serial.begin(9600);
analogReadResolution (12);
analogWriteResolution (12);
}
Float voltage = 0;
Unsigned int sensor value =0;
// the loop rotine runs over again forever:void loop()
{
// read the input on analog pin 0: sensorValue  analogRead(A0);
Voltage =(sensor Value *0.8/ 4095);
Seria.prinIn(voltage);
Delay(20);
}
```

3.5. MATLAB /Simulink

MATLAB stands for matrix laboratory. MATLAB is a high -level language for technical computing. MATLAB integrates computation, visualization and programming in an easy to use environment where solutions and problems are expressed in familiar mathematical notation [43]. Typically MATLAB includes:

- Math and computation.

- Algorithm development.
- Modeling, simulation and prototyping.
- Data analysis, exploration and visualization.
- Scientific and engineering graphics.

MATLAB is an interactive method whose basic data element is an array that does not need dimensioning. It allows us to explain many technical computing problems, those with matrix and vector formulations in a fraction of the time [44]. MATLAB features a family of application –specific solutions called toolboxes. Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems [38, 39]. The system consists of five main parts which I described below:-

1. The MATLAB Language: - It is a high- level matrix/ array language with control flow statements, data structures, functions, input/ output and object- oriented programming features.
2. The MATLAB working environment: - MATLAB is the set of tools and facilities that work with as the MATLAB user or programmer. It includes facilities for and importing and exporting data and managing the variables in MATLAB workspace. It also includes tools for developing, managing, debugging and profiling M-files, MATLABs applications.
3. Handle graphics:- In the MATLAB graphics system, it includes high- levels commands for 2 dimensional and 3 dimensional data visualization, image processing, animation and presentation graphics. It includes low level commands that agree to us to fully customize the appearance of graphics as well as to build complete graphical user interfaces in MATLAB application.
4. The MATLAB mathematical function library: - It is a vast gathering of computational algorithms ranging from elementary functions like addition, sine, cosine, logical and complex arithmetic, Fast Fourier Transform (FFT) etc.
5. The MATLAB Application Program Interface (API):- It is a library that allocates us to write C and Fortran programs that interact with MATLAB.

Simulink is an input/ output device GUI block diagram simulator, which are drawn on a screen as a block diagrams. It is a data flow graphical programming language tool for modeling, simulating and analyzing multi domain systems. Simulink contains a library editor of tools from which user can build input/ output devices and continuous and discrete time model simulations [40].

Chapter 4

4. Data Acquisition & Processing

This chapter shows the result of the Facial EMG signal, which was conducted in the lab. In the experiment, I used an offline Facial EMG raw data signal. My work is related to Signal processing i.e. removal of unwanted signal and noise from the raw EMG Signal. The signal processing for converting raw signals to signals that represents the intensity of Facial movements. In every step of signal processing, every step is studies carefully and analysis that part properly. I have taken the two raw facial EMG signals from the Facial muscles. Appendix B shows a Matlab code for the Zygomaticus muscle; in my sequence I have show 10000 values in my sequence. The results below from section 4.1 to 4.6 show the signal processing of zygomaticus muscle and later I discuss the signal processing of Frontalis muscle. During our experiments we put electrodes on desired Facial muscles and other electrode is used for common reference electrode (at border of hair line) [3, 22].

4.1. Raw EMG Signal (Zygomaticus Facial Muscle)

An unfiltered and unprocessed signal detects the superposed motor unit action potential (MUAP) known as a raw EMG signal [19]. When the facial muscle is relaxed, a more or less noise free EMG Baseline can be seen. The raw EMG baseline noise depends on many factors especially the environment noise, the quality of the given detection state and EMG amplifier [19]. Figure 11 represents a raw Facial EMG signal. The raw Facial EMG recording contains very vital information and may serve as an initial objective information and documentation of the Facial muscle innervation. Figure 12 represents a zoom in on a raw EMG signal sample with index from 2000 to 6000. An important point is that these signals are measured from a **Zygomaticus Facial Muscle** and it is easily seen the change of facial muscles observe in the diagram.

4.2. Notch Filter

A notch filter is a filter that passes all frequencies except those in a stop band centered on a center frequency. It has a flat amplitude response at all frequencies except for the stop band on either side of the center frequency [23]. The main purpose of notch filter in my case i.e. for suppression of power line interference. Figure 13 shows a plot of the output of the notch filter, when raw signal pass through a notch filter.

4.3. Band Pass Filter

It is a filter that allows signals between two specific frequencies to pass and that discriminates all other frequencies present in the signal. The reason to apply a high pass filters i.e. to remove the other frequencies of movement of facial activities or other artifacts. I have use 4^{th} order butter worth filter with a band pas frequency from 10 to 200 (Hz). Figure 14 shows a plot of the output of the band pass Filter. The Butterworth filter is a kind of signal processing filter to have as flat frequency response as possible in the pass band.

4.4. Full Wave Rectification

In a third step, we have done the rectification. In this step all negative amplitudes are converted to positive amplitudes, the negative spikes are moved up to plus or reflected by the baseline [41]. The main effect is that standard amplitude parameters like mean, peak/ max value and area can be applied to the curve (raw EMG has a mean value of zero). Figure 15 show a full wave rectified EMG Signal. In MATLAB environment, taking the absolute value of the signal is called Full-wave Rectification. The rectification step is essential for getting the shape or envelope of the EMG signal. One might believe the envelope could be captured by simply low passing the un-rectified signal to smooth it [1, 19, 41].

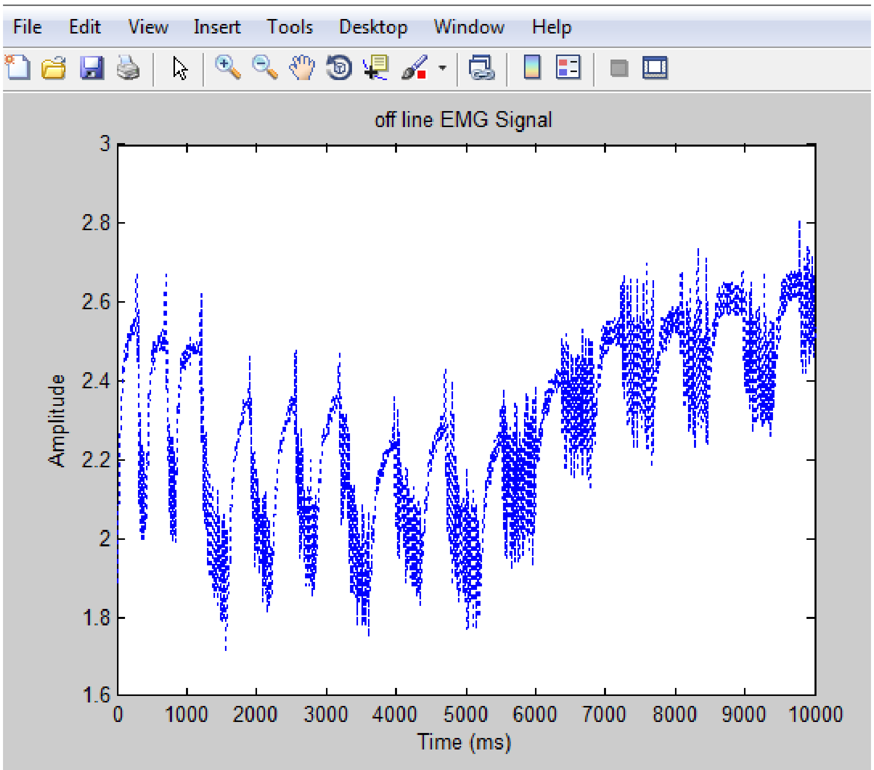

Figure 11. Raw Facial EMG Signal.

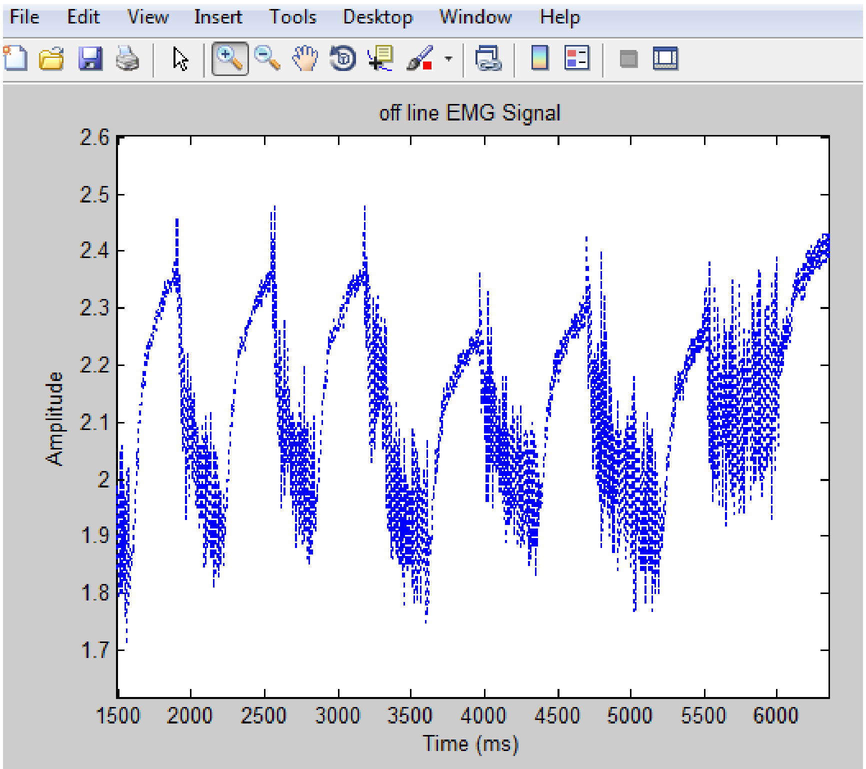

Figure 12. Raw EMG signal (interval-sample range 2000-6000).

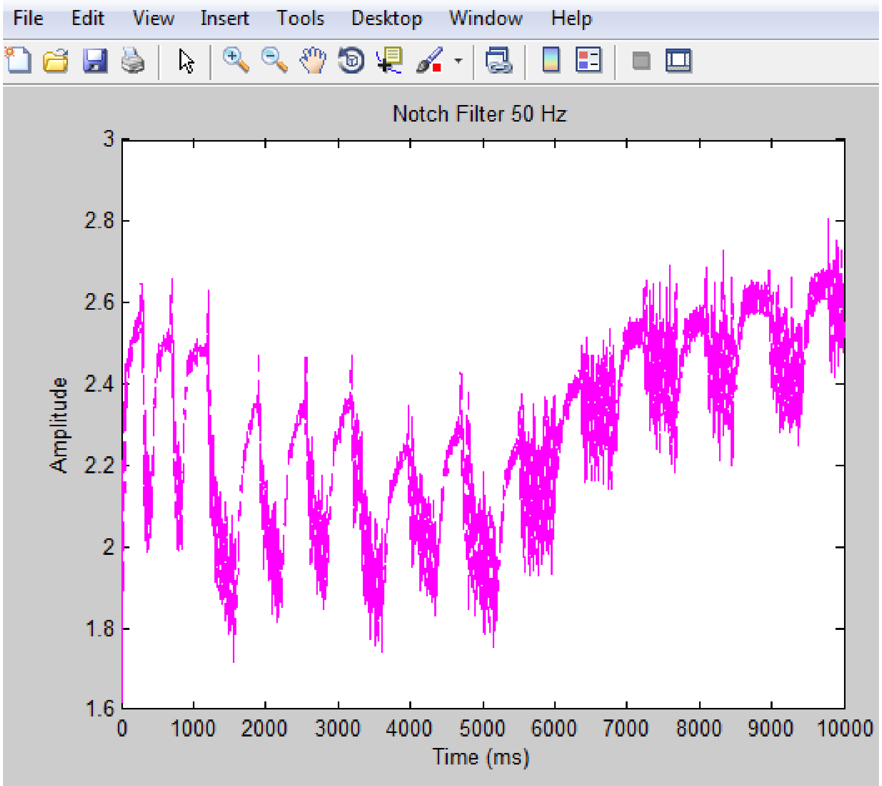

Figure 13. Effect of the Notch Filter.

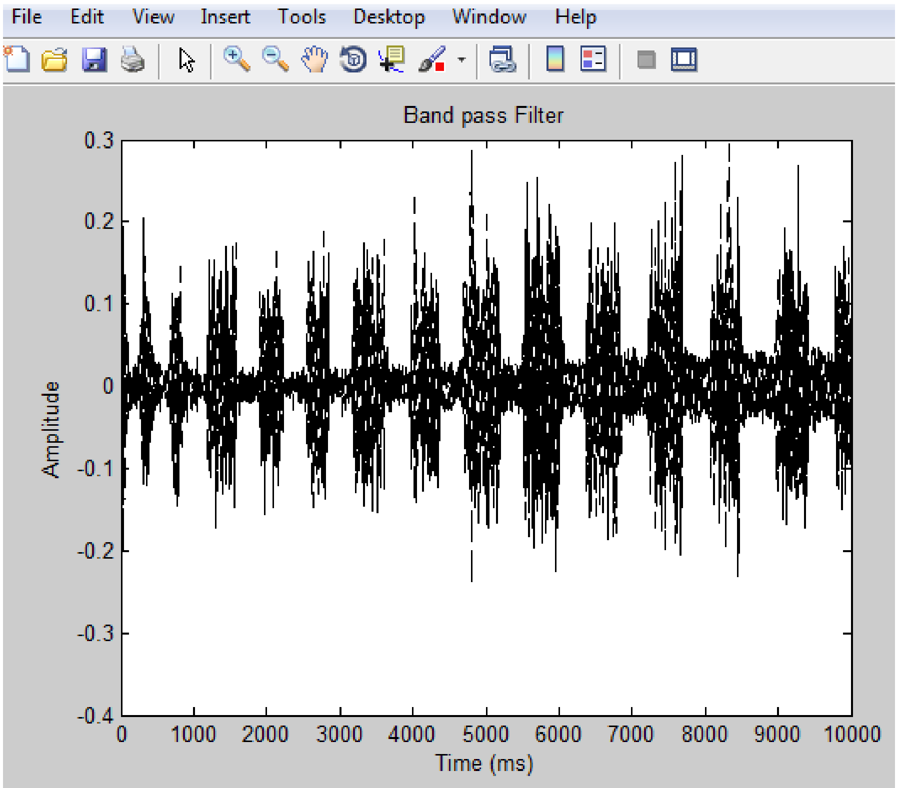

Figure 14. Output of the Band Pass Filter.

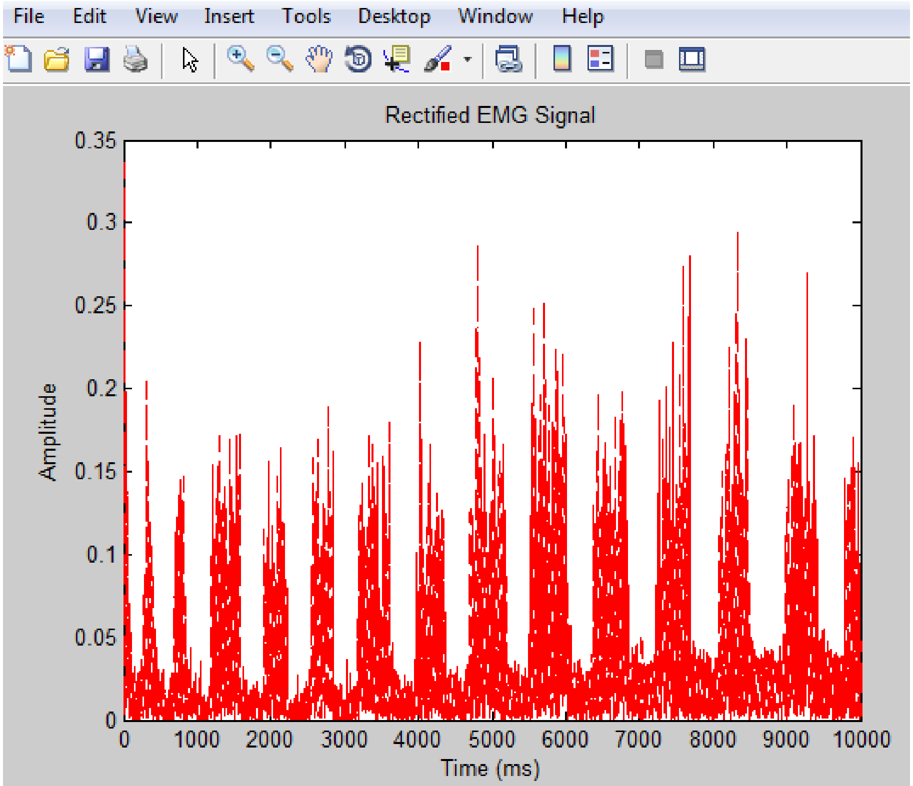

Figure 15. Rectified EMG Signal.

4.5. Output Filtering

In this section, we use digital filter is a system that performs mathematical operations on a sampled, discrete- time signal to reduce or enhance certain aspects of that signals. It is used for separation of signals that have been combined and restoration of signals that have been distorted. In our model we use Low pass filter, Fig 16. shows the result of Low pass Filter.

4.6. Time Frequency Analysis

The frequency content of the EMG may be analyzed using Fast Fourier Transform (FFT). It is useful to use a FFT in order to identify certain characteristics of the frequency contents of the Facial EMG signal. Fourier Transform and its inverse provide a relation between the time domain and the frequency domain. It allows us to find the power spectrum of the entire signal. A fast Fourier Transform (FFT) is an efficient algorithm to compute the discrete Fourier Transform (DFT); it becomes simple to jump between time domain and the frequency domain of a signal. Figure 17 shows a figure of FFT of a raw EMG Signal.

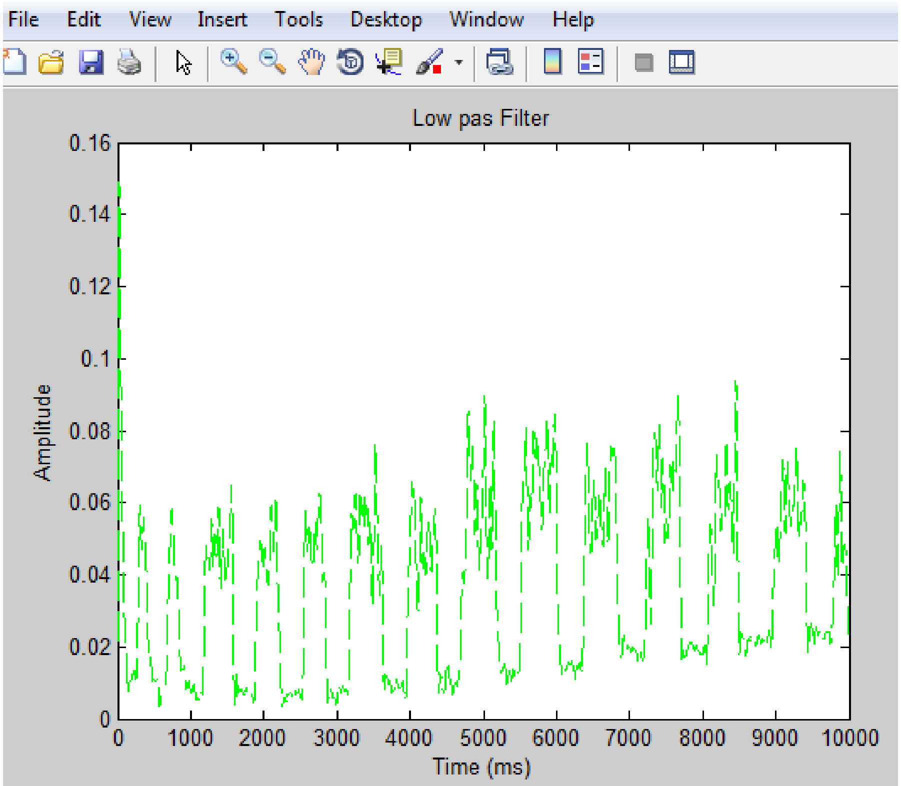

Figure 16. Low Pass Filter.

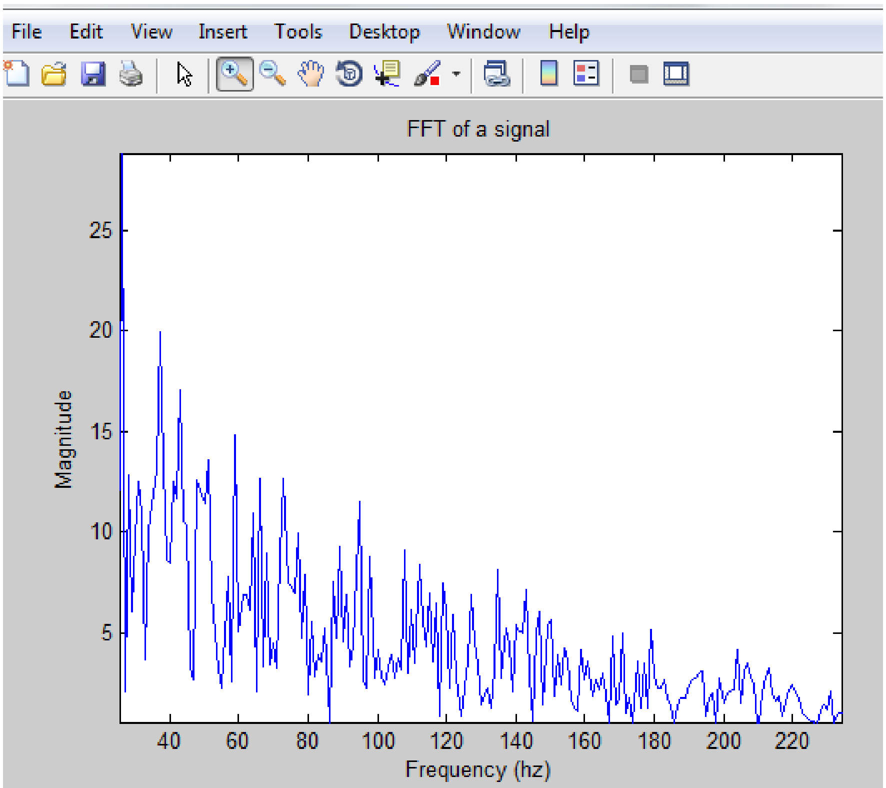

Figure 17. FFT of a Facial EMG.

4.7. Signal Processing (Frontalis Muscle)

After analysis of zygomaticus Facial Muscles, the Frontalis Facial muscle signal is analyzed. I take off- line EMG signal from this muscle and see the intensity of the signal. In this we have used the same matlab code for signal processing but with little changes in cut off frequency and sampling frequency. Appendix C shows a Matlab code for frontalis facial muscle. Figure 18, 19 and 20 show the signal processing in steps for the Frontalis Facial Muscle.

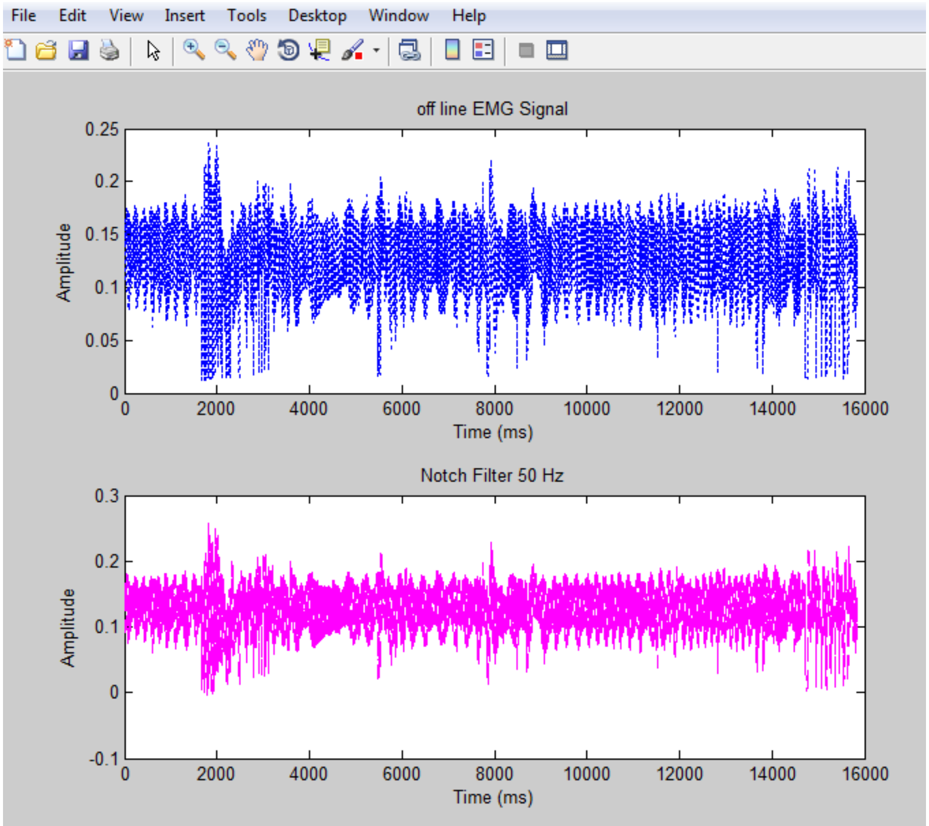

Figure 18. Signal Processing of Frontalis muscle (incl notch filter).

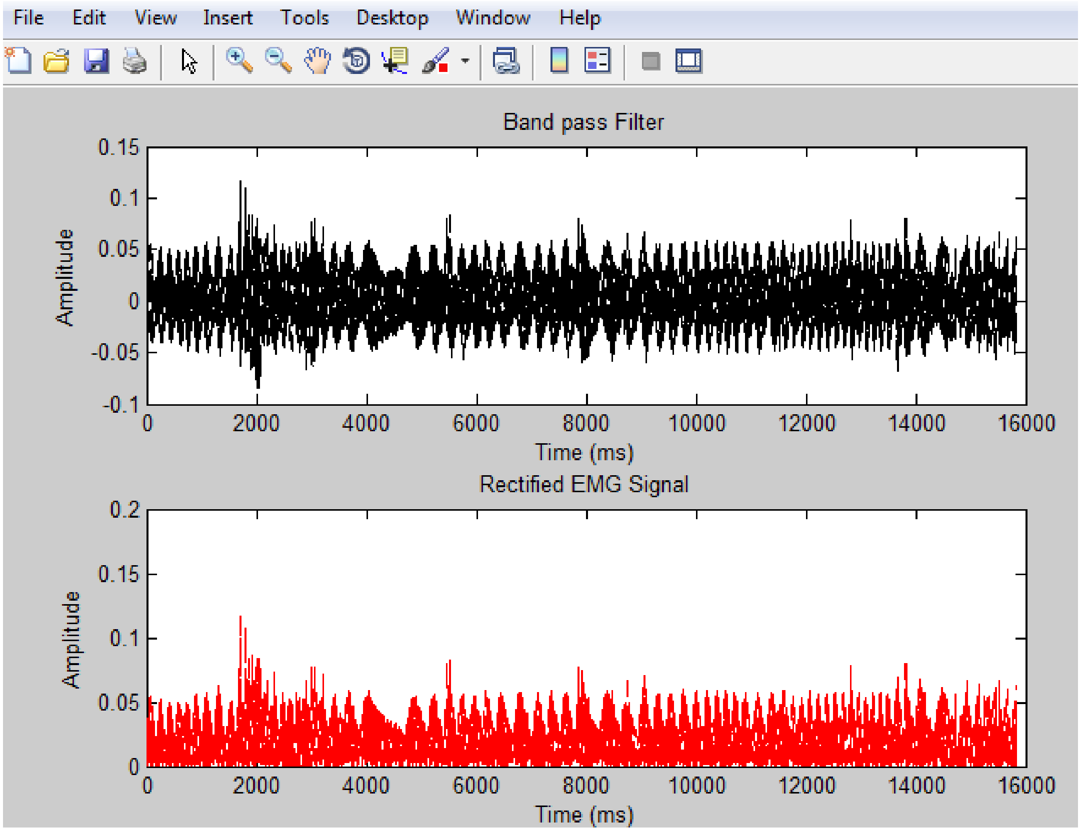

Figure 19. Signal Processing of Frontalis muscle (band pass filtering and rectifying) .

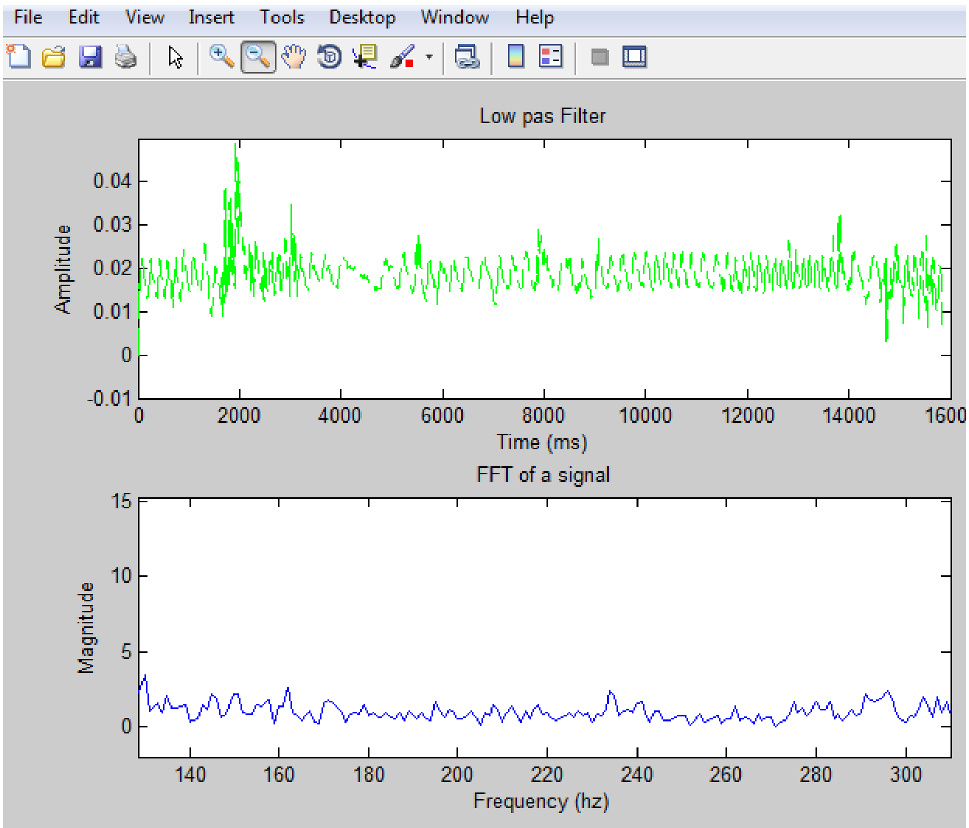

Figure 20. Signal Processing of Frontalis muscle (FFT magnitude).

4.8. Smoothing Filter

Rectified Signals were converted to the intensity signal by using smoothing filter. A root mean square (RMS) filter was used for the task in the offline analysis. It is based on the square root calculations and it reflects the mean power of the signal [1, 19, 41]. Figure s 21 shows a plot of output of RMS filter. This stage comes after the stage of rectification. Actually, the RMS algorithm can work also for bio- polar signals, without rectification, so simplifying the solution.

4.9. Simulink Model

During an experiment, I designed a simulink model for signal processing. To design a model in simulink is easier and it's easy to use as comparison to MATLAB script. In my case, we cannot connect panda board to the simulink environment, after that we swap to MATLAB environment. But I have designed a model which I show in Figure 22.

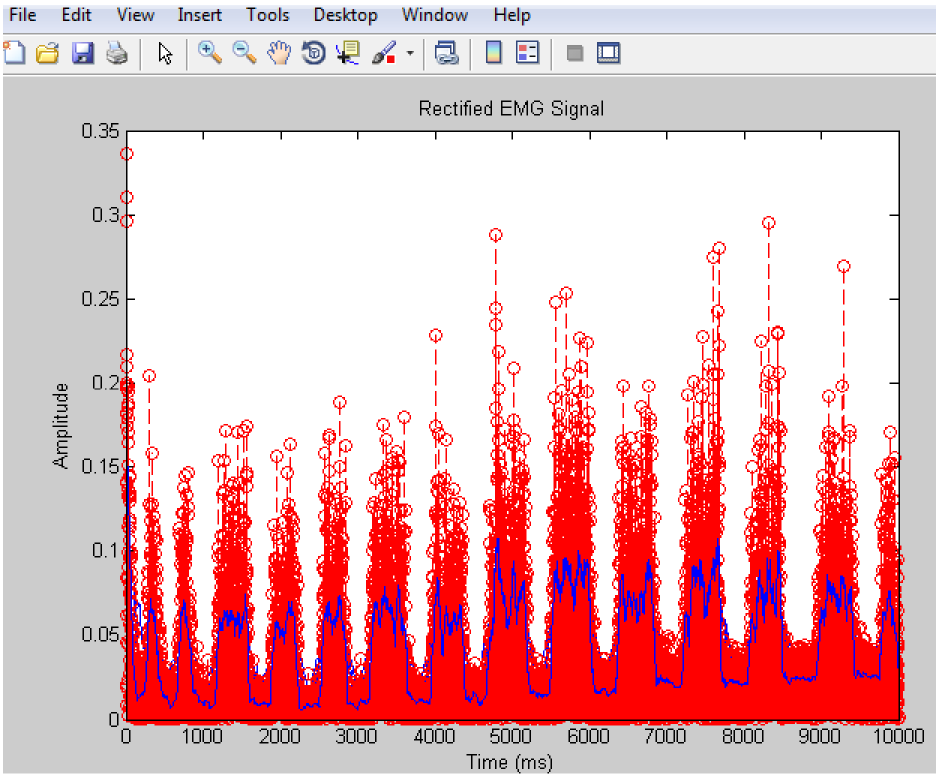

Figure 21. Root Mean Square.

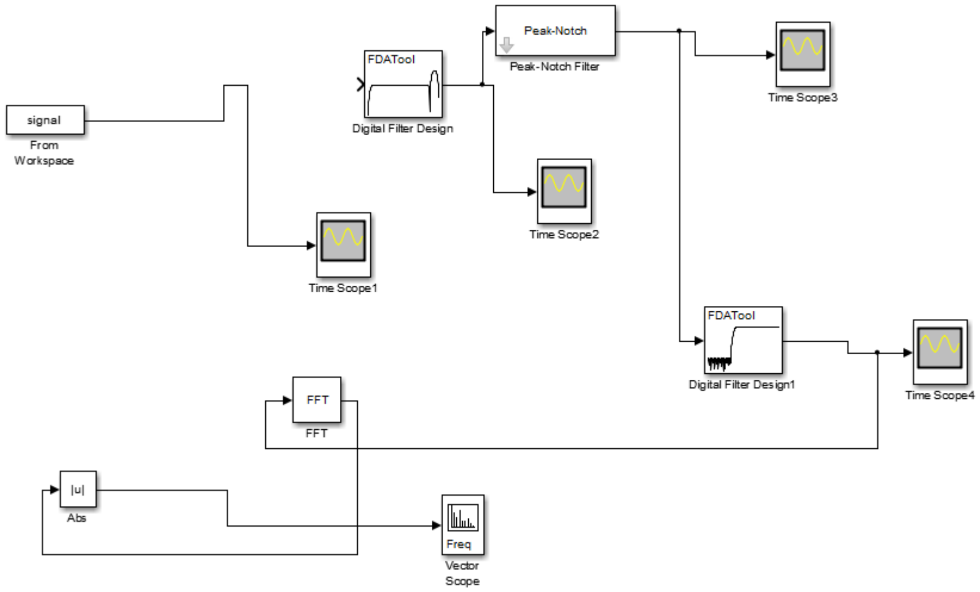

Figure 22. Simulink model.

Chapter 5

5. Result & Conclusion

5.1 Result

Experiments was carried out with the goal to gather data for our Facial EMG expressions. The data was then studied with the goal to find out whether or not the classification would be practicable, in respect of using it for commercial purpose and thus to show how we can record Facial EMG Signal by using bio electric SoC board. Also- MATLAB based signal processing software scripts were developed, evaluated and tuned for real- time EMG- signal intensity monitoring for possible measuring of pain (possible other feeings).

Results showed that when there is a change in a Facial Muscles, we can record these EMG signals by using bio electric SOC. The results are not taken from the patients in ICU or neonates, because our goal/ task are to first remove the unwanted signals from the facial EMG. After that our task is to remove the noise from these signals and analysis these signals using FFT. These results are taken by us in our lab, so the results are not 100 % accurate but first of all our main step is to record the Facial EMG Signals. We have taken the off line EMG signals from Frontalis Muscle and Zygomaticus muscles.

5.2. Conclusion

EMG measurement technique is suitable for clinic purpose to detect the pain because when someone has a pain, than there is a change in their facial muscles and with this method it is easily detect and analysis. On the other hand Facial Action Coding System (FACS) is a time consuming technique and needs expert knowledge or training. The performance of our current work still shows a need for further improvement.

5.3. Future work

If I will get a chance to work on this project, than I will record these signals on a patient. With the team of Doctors and University team we will analysis these signals whether these signals are showing Emotional Pain/ hurt or it's fake one. Our main goal is to analysis the Emotional Pain/ Hurt of patients in Intensive Care Unit (ICU) and Neonates. It is a challenge for us to distinguish between Pain VS Cry in Neonates. And another important issue is that the Neonates growing at a very fast rate, so we have to change the scale according to their age. The importance of having a system is to automatically detect the pain is very important as could greatly improve the efficiency and overheads associated with monitoring patient progress in hospital setting.

In addition to this, we hope to look at other modes of detecting pain from patient by using Video camera recording. The utilization a system where a patient is in bed needs to be examined as well. This introduces added complexities as the face will also be partially occluded due to the angle of patients face to the camera. Here Facial Action Coding System help us a lot to understand the Emotional Pain / hurt of a patient. In this system we will employ an Active Appearance Model (AAM) based system which uses AAM to detect to track the face and extract the visual appearances. The Support Vector (SVM) can be used to classify the Action unit (AU) and Pain.

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Appendix A

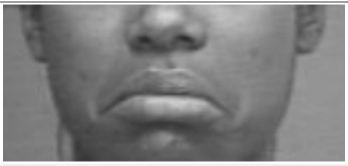
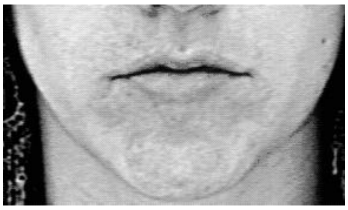
FACS

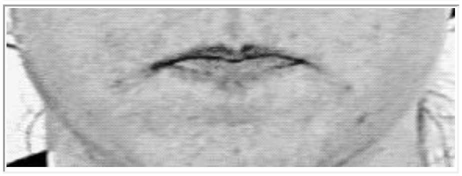
http://www.cs.cmu.edu/~face/facs.htm

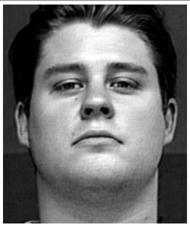
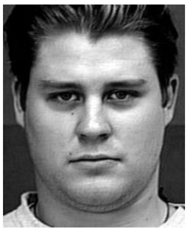
FACS - Facial Action Coding System

(Ekman and Friesen 1978)

AU	Description	Facial muscle	Example image
1	Inner Brow Raiser	Frontalis, pars medialis	
2	Outer Brow Raiser	Frontalis, pars lateralis	
4	Brow Lowerer	Corrugator supercilii, Depressor supercilii	
5	Upper Lid Raiser	Levator palpebrae superioris	
6	Cheek Raiser	Orbicularis oculi, pars orbitalis	
7	Lid Tightener	Orbicularis oculi, pars palpebralis	
9	Nose Wrinkler	Levator labii superioris alaquae nasi	
10	Upper Lip Raiser	Levator labii superioris	

11	Nasolabial Deepener	Zygomaticus minor	
12	Lip Corner Puller	Zygomaticus major	
13	Cheek Puffer	Levator anguli oris (a.k.a. Caninus)	
14	Dimpler	Buccinator	
15	Lip Corner Depressor	Depressor anguli oris (a.k.a. Triangularis)	
16	Lower Lip Depressor	Depressor labii inferioris	
17	Chin Raiser	Mentalis	
18	Lip Puckerer	Incisivii labii superioris and Incisivii labii inferioris	
20	Lip stretcher	Risorius w/ platysma	

22	Lip Funneler	Orbicularis oris	
23	Lip Tightener	Orbicularis oris	
24	Lip Pressor	Orbicularis oris	
25	Lips part**	Depressor labii inferioris or relaxation of Mentalis, or Orbicularis oris	
26	Jaw Drop	Masseter, relaxed Temporalis and internal Pterygoid	
27	Mouth Stretch	Pterygoids, Digastric	
28	Lip Suck	Orbicularis oris	
41	Lid droop**	Relaxation of Levator palpebrae superioris	
42	Slit	Orbicularis oculi	
43	Eyes Closed	Relaxation of Levator palpebrae superioris; Orbicularis oculi, pars palpebralis	

44	Squint	Orbicularis oculi, pars palpebralis	
45	Blink	Relaxation of Levator palpebrae superioris; Orbicularis oculi, pars palpebralis	
46	Wink	Relaxation of Levator palpebrae superioris; Orbicularis oculi, pars palpebralis	
51	Head turn left		
52	Head turn right		
53	Head up		
54	Head down		
55	Head tilt left		
56	Head tilt right		

57	Head forward		
58	Head back		
61	Eyes turn left		
62	Eyes turn right		
63	Eyes up		
64	Eyes down		

*AUs (Action Units) underlined bold are currently recognizable by AFA System when occurring

**The criteria has changed for this AU, that is AU 25, 26 and 27 are now coded according to criteria (25A-E) and also AU 41, 42 and 43 are now coded according to criteria of intensity.

Appendix B: Matlab Code for zygomaticus muscle

```
%% Upload gernated EMG Signal name as emgrawdata
x =load ('G:\Matlab 2013a\ojaemg\offlineEMGsignal2\zygoemgrawdata');
figure (1)

plot (x,'b:');
title ('off line EMG Signal')
xlabel ('Time (ms)')
ylabel ('Amplitude')

%% Notch Filter (50 HZ)
filt3= fdesign.notch(4,0.1,10);  %% sampling frequency =500
h3 = design (filt3);
cleaned_emg= filter(h3,x);
figure (2);
plot(cleaned_emg, 'm--');
title ('Notch Filter 50 Hz')
xlabel ('Time (ms)')
ylabel ('Amplitude')
%% Band Pass Filter
Fss= 500;
Fnn= Fss/2;
[b,a]= butter(4,([10  200]/Fnn));
filtered_Data=filtfilt(b,a,cleaned_emg);
figure (3)
plot (filtered_Data, 'k--');
title ('Band pass Filter')
xlabel ('Time (ms)')
ylabel ('Amplitude')

 %% Rectification
rec_x=abs(filtered_Data-mean(filtered_Data));
figure (4)

plot(rec_x, 'r--');
hold on
xlabel('Time (ms)')
ylabel('Amplitude')
title ('Rectified EMG Signal')
```

```
%% Filtering
%% 4th order Butterworth low pass filter

Fs= 500;    %% sampling frequency
Fc= 10;       %% cut off frequency
N=4;  %% filter order
[b,a]=butter(4,Fc/(Fs/2),'low');
filter_x= filtfilt(b,a,rec_x);
figure (5)
plot(filter_x,'g--');
hold on
xlabel('Time (ms)')
ylabel('Amplitude')
title ('Low pas Filter')
figure (6)

%% FFT of Facial EMG Signal

y= fft(filter_x);
y_mags = abs (y);
plot (y_mags)
xlabel ('Frequency (hz)')
ylabel ('Magnitude')
title ('FFT of a signal')
```

Appendix C: Matlab Code for frontalis muscle

```
%% Upload gernated EMG Signal name as emgrawdata
x =load ('G:\Matlab 2013a\ojaemg\emgrawdata');
figure (1)
subplot (2,1,1)
plot (x,'b:');
title ('off line EMG Signal')
xlabel ('Time (ms)')
ylabel ('Amplitude')

%% Notch Filter (50 HZ)
filt3= fdesign.notch(4,0.1,10);
h3 = design (filt3);
cleaned_emg= filter(h3,x);
figure (1);
subplot (2,1,2)
plot(cleaned_emg, 'm--');
title ('Notch Filter 50 Hz')
xlabel ('Time (ms)')
ylabel ('Amplitude')
%% Band Pass Filter
Fss= 600;
Fnn= Fss/2;
[b,a]= butter(4,([20  250]/Fnn));
filtered_Data=filtfilt(b,a,cleaned_emg);
figure (2)
subplot (2,1,1)
plot (filtered_Data, 'k--');
title ('Band pass Filter')
xlabel ('Time (ms)')
ylabel ('Amplitude')

 %% Rectification
rec_x=abs(filtered_Data-mean(filtered_Data));
figure (2)
subplot (2,1,2)
plot(rec_x, 'r--');
hold on
xlabel('Time (ms)')
ylabel('Amplitude')
title ('Rectified EMG Signal')
```

```
%% Filtering
%% 4th order Butterworth low pass filter

Fs= 600;     %% sampling frequency
Fc= 20;        %% cut off frequency
N=4;  %% filter order
[b,a]=butter(4,Fc/(Fs/2),'low');
filter_x= filtfilt(b,a,rec_x);
figure (3)
subplot (2,1,1)
plot(filter_x,'g--');
hold on
xlabel('Time (ms)')
ylabel('Amplitude')
title ('Low pas Filter')
figure (3)
%% FFT of Facial EMG Signal

y= fft(filter_x);
y_mags = abs (y);
subplot (2,1,2)
plot (y_mags)
xlabel ('Frequency (hz)')
ylabel ('Magnitude')
title ('FFT of a signal')
```