Emotion Recognition With Forearm Based Electromyography

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Declaration of Authorship

We, Muhammad Shihab Rashid & Zubayet Zaman, declare that this thesis titled, 'Emotion Recognition With Forearm Based Electromyography' and the work presented in it are our own. We confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.

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Abstract

Electromyography is an unexplored field of study when it comes to alternate input methods while interacting with a computer. Gesture based interaction has become widely popular because of its ease of use. In this paper we discuss about two layers of Electromyography. Whether EMG can be used as an alternate input modality and can give better experience that traditional devices and in the second layer we try to talk about whether EMG data can be used to detect human emotions such as anger or fear. We have prepared an experiment to compare two input methods, one is traditional one and another our muscle wearable device. Then we plan to evaluated the results to find , users have better experience with our wearable device.

Contents

Chapter 1

Introduction

Electromyography means the recording of the electrical activity of muscle tissue, or its representation as a visual display or audible signal, using electrodes attached to the skin or inserted into the muscle.[15]. Human body is comprised of lots of nerves and sensors, and they pass electric signals throughout the body. Electromyography is the study of these signals and how these impact different aspects.
While body-worn computer systems become more and more popular, the question of the ideal input devices is still open. Since output devices are often decoupled from the input device, keyboard and touch-screen based solutions are inappropriate. A combination of speech and gesture interfaces seems most promising. While speech is the most intuitive way of entering information in situations in which the computer is perceived as communication partner, gestures are especially suited for spatial or silent and inconspicuous interaction. Gestures could be performed with the whole arm, the hand or the fingers: small sized gestures are generally more appropriate for wearable computing, since large scale gestures are tiring for the user and humans are specialized in fine-grained manipulation with their fingers. Therefore, interfaces allowing for fine-grained gestures and manipulation of virtual objects seem promising. Possible application scenarios are controlling smart glasses or watches with subtle finger motions and gestures. The application of sensors directly at the fingers itself e.g., with data gloves, is inappropriate in daily-life situations. As a result, multiple approaches have been proposed to sense finger motion distantly. This includes body-worn cameras, wrist-worn depth cameras, measuring the movement of the tendons or directly measuring the muscle activity via Electromyography (EMG). The EMG approach and also the related tendon approach make use of the fact that most of the major finger

muscles are located [7] at the forearm and thus allow for sensing finger motion by attaching sensors around the forearm instead of the fingers. However, inferring the finger motion from the EMG is a challenging task. The positioning of the sensors is crucial for acquiring the right signals. Furthermore, there are interpersonal differences in the anatomy of the muscles and tissue layers. Wearable EMG based interfaces should not require exact positioning of electrodes and ideally autocalibrate themselves.

Chapter 2

Problem Description

2.1 Problem Identification

As traditional interaction methods have become outdated and monotonous, researchers are constantly finding alternate and better interaction methods. With the rise of wearable devices, users can now easily interact with computers. But yet, status quo has some restrictions. The research problem can be categorized into the following:

- **Monotonisity of Traditional Input Devices:** The traditional input devices that we see such as keyboard and mouse have become monotonous. They have been in use for a long time and researchers are longing for an alternate design to interact with a computer

- **Restrictions of Traditional Input Devices:** Keyboard and Mouse cannot detect emotions or user expressions which have become an exciting prospect recently. They have certain limitations recognizing human emotions.

- **Unexplored Field:** In computer science everyday, newer things are being brought to life, because it is a fast changing area, researchers are always looking for new and exciting things to work with. Electromyograpy is usually used in medical field with huge and expensive machinery. But to use our muscle data to interact with a computer is relatively new and unexplored idea.

- **Limiting User Experiences:** People want new and exciting things to interact with everyday, and they want their gaming experiences to be as realistic and as exciting as possible. But with current methodologies, they have limiting user experience, because one can only do so much with gestures and sensors.

2.2 Existing Methodologies

The existing methodologies to interact with a computer are:

- **Traditional Devices:** Such as keyboard, mouse, joystick etc. They have very limiting capabilities and functionalities.
- **Gesture Based Interaction:** These include hand gestures, body and face gestures, head gestures etc. These gesture based interaction can be subdivided into the following:
  - Sensor Based: These sorts of interaction is possible by getting values by different sensors. Sensors can vary from as wide as accelerometer to as specific as force resistive sensors.
  - Image Based: Image based gesture interaction includes capturing image using a camera and then applying image processing algorithms to detect different gestures.
- **Eye Tracking:** A new form of interacting with a computer has seen light which is eye tracking. Camera or webcam is used to detect the movement of eye to output it as interaction such as scrolling the page, moving to next page etc.

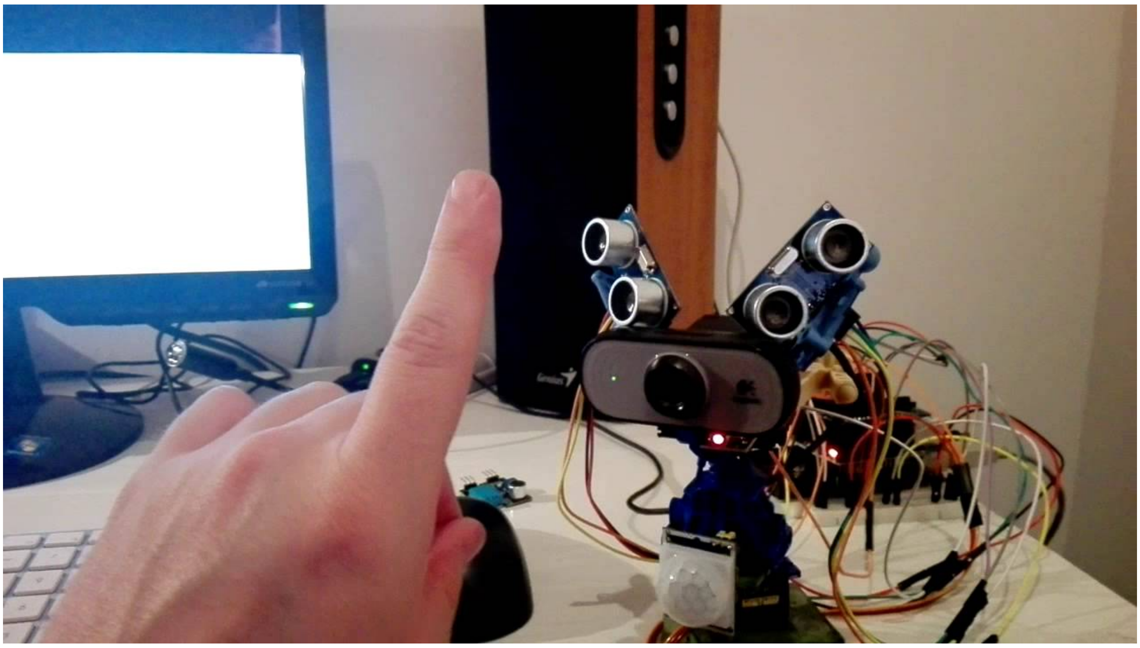


Figure 2.1: Gesture Based Devices

But these have some limitations, which are:

- These are fixed methods, gestures can rarely be changed

Chapter 3

Background Study

3.1 Sensing Muscles With EMG

Human skeletal muscles are made up of muscle fibers attached [14] to bone by tendons. These muscles contract to create skeletal movement. To contract a muscle, the brain sends an electrical signal through the nervous system to motor neurons. These motor neurons then transmit electrical impulses known as action potentials to the adjoining muscle fibers,[4] causing the muscle fibers to contract. The combination of a motor neuron and the attached muscle fibers are known as a motor unit. Each muscle is made up of many motor units. During muscle contraction, some subset of a muscle's motor units is activated. The sum of all the electrical activity in a motor unit during contraction is referred to as a motor unit action potential (MUAP).

Electromyography (EMG) measures the MUAP as an electrical potential between a ground electrode and a sensor electrode. EMG can measure signals either directly within the muscle (invasive EMG) or on the skin above a muscle (surface EMG). Invasive EMG is very accurate in sensing muscle activation, but is impractical for human-computer interaction applications as it requires needle electrodes to be inserted through the skin and directly into the muscle fibers. Surface EMG, while less accurate, only requires that conductive sensors be placed on the surface of the skin. Surface EMG is fundamentally noisier than invasive EMG since [12] [13] MUAPs must pass though body tissues such as fat and skin before they can be captured by a sensor on the surface. Due to the high sensitivity of EMG sensors required to detect these signals, they also typically detect other electrical phenomena such as activity from other muscles, skin movement over muscles, and environmental noise. For more information on the state-of-the-art in

surface electromyography. In our work, we explore the use of surface EMG for muscle sensing, and imagine people wearing future muscle-computer interaction devices as a small strap or band of sensors slid on to the upper forearm.
The EMG signal is an electrical potential, or voltage, changing over time. The raw signal is an oscillating wave with an amplitude increase during muscle activation. Most of the power of this signal is contained in the frequency range of 5 to 250 Hz. A typical statistic computed over the raw EMG signal for diagnosis of muscle activity is the windowed root mean squared (RMS) amplitude of the measured potential. This measure has typically been employed for diagnostic purposes such as evaluating muscle function during rehabilitation after a surgery or for measuring muscle activation to assess gait. RMS amplitude is a rough metric for how active a muscle is at a given point in time.

3.2 Emotions

"Emotion" is an idea or expression that can define the current state or condition of human mind or behavior.[6] It can be characterized by psychological and physiological expressions, biological reactions, and mental states. Emotion is one of the fundamental components or characteristics of being human. Emotion can be derived from human experiences and expressions to represent different emotional states such as anger, disgust, fear, happiness, sadness, surprise, excitement and so on. It is understandable that a wide range of user moods play an important role in every computer related and goal oriented activity, from using drawing application and editing photos in a photo manipulation app to browsing web pages and sending a message and making an online purchase. The way the user carries out a job or uses an application is highly influenced by his emotional states. Emotion recognition refers to the identification of emotional states. There are several well-known methods which can be effectively used for detecting the mood of a person.
Firstly, we all know that brain is the most fundamental source of emotion and the best way to measure all sort of neurological changes is the electroencephalogram (EEG). In the recent years, using magneto image reasoning (MRI) also offers great promise for monitoring emotion [1]. Facial expressions play a vital role both for verbal and nonverbal

communication. And so, due to the change in user's mental state a significant change goes on the facial muscles and analyzing the data achieved from these expressions can be used to detect his/her emotion. It requires neuroscience, digital image processing, pattern recognition and vast amount of analysis and processing of collected data using complex algorithms to generate probable emotion which is difficult to implement in smaller hardware or devices. Hence the necessity to detect emotion in some other convenient ways arises.

Thirdly, mood can also be detected from audio signals. The vocal aspect of a message or conversation carries significant variations or emotional information. If we do not consider how a sentence was verbally spoken, the meaning we get may not be the one intended. From the input audio signals pitch, intensity, and pitch contours were estimated and treated for feature extraction which was finally used to building the classifier .

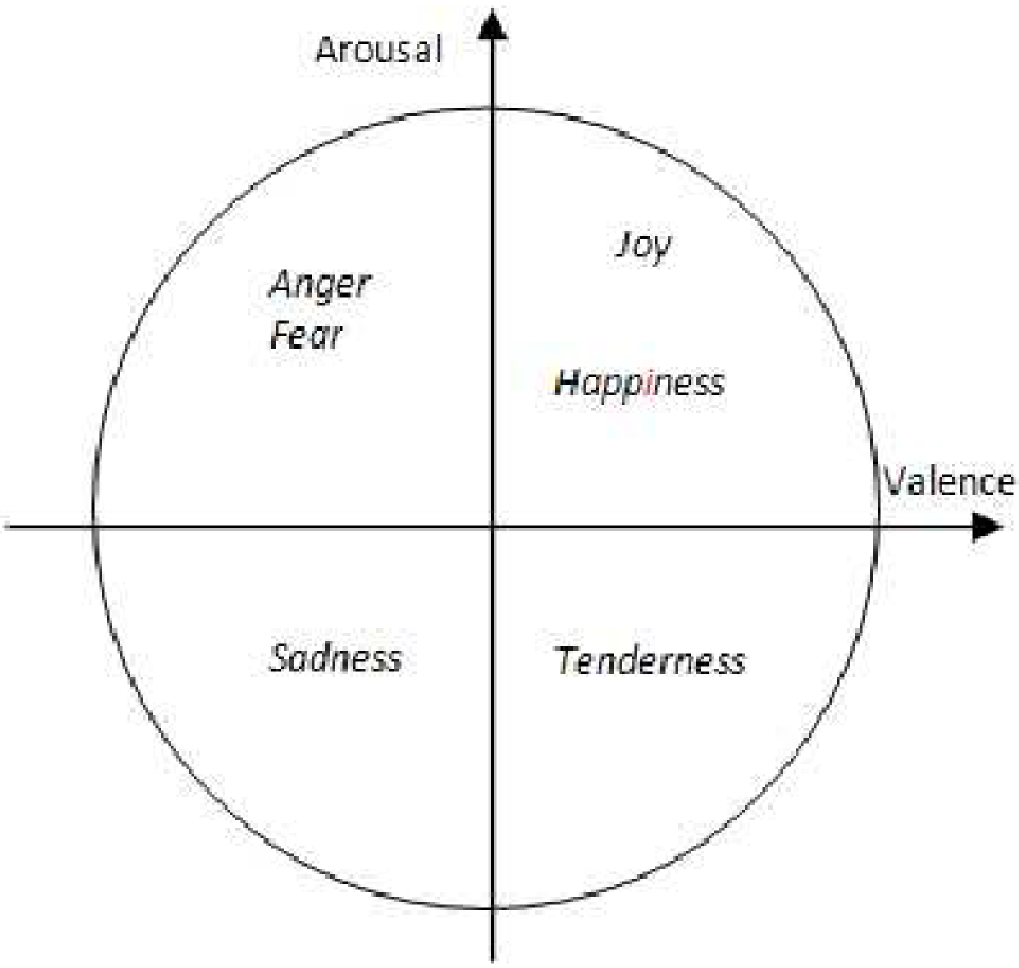
Another new method is Multimodal Emotion Recognition. [3] Voice, gesture, and force-feedback etc. can also be used for identifying emotion instead of using only keyboard and mouse. The multimodal approach is a lot more dynamic but it has some constraints which is still an ongoing research. It has to correlate multiple types of inputs and finally integrate with probabilistic models . And next there is another approach using pressure sensing keyboards and keystroke dynamics [8] producing substantial accurate results.

Some common sensors found on modern smartphone include proximity sensor, gyroscope, barometer, accelerometer, Hall Effect sensor, ambient light sensor and GPS. The sensor that is responsible for detecting the orientation and acceleration of the device is accelerometer [9]

Chapter 4

Related Works

There are different classification systems for emotion. According to Plutchik emotion can be of eight types. Anger, fear, sadness, disgust, surprise, anticipation, acceptance and joy. All other emotions can be formed by mixing these basic emotions. The most widely used system is Russel's bipolar system where emotion is classified into two categories: Arousal and Valence . [?] Arousal ranges from sad/angry to excited/joyful and valence ranges from negative to positive. In this paper we have chosen two contrasting emotions such as Angry and Relaxed so that we can differentiate between the emotions. The second reason being, in the applications of EMG such as in gaming, people usually express these two types of emotions.



Although detection of human emotions in the area of human computer interaction is a newer methodology itself, there are some significant research done in this area. But whether emotion detection can be done through electromyography data is still to be answered. But similar mechanisms has been used in detecting emotions in recent years. They are presented below.
Firstly, as per human anatomy, brain is the most fundamental source of emotion and best way to measure the neurological changes. This type of process is called Electroencephalography or EEG. In recent years MRI also shows great promise in detecting human emotion. In Liu et. al. showed that using a brain signal sensor, emotions can be detected in the valence-arousal two dimensional model. But the author proposes some challenges in working with brain sensors. The sensors are noisy as our brain handles different functions at a certain point in time. So the separation of noise with actual data is quite difficult.
Secondly facial muscles or expressions plays a vital role for both ver-

bal and nonverbal communication. Due to changes in mental state, users facial expressions also change. But these expressions are somewhat forced, it does not happen naturally. Plus the added challenge of analysis and processing of huge data with complex algorithms to generate probable emotion is difficult to implement in smaller hardware or devices. So a more convenient way is necessary.
Third, audio signals or voice can also play a part. Users vocal chords can carry significant variations or emotional information. From the pitch, intensity and pitch contours are estimated. But speech data most times do not correlate with the meaning the user intended to say. Most times it is misinterpreted by computer.
Newer ways of emotion recognition such as haptile feedback which is based on users touch input seem promising. But users touch contain very little information regarding emotional activity which proposes as a problem. In the authors propose that emotions can be expressed depending on users sitting position and also using smartphones different sensors. But these methods are dependent on the user having a smartphone or sitting at a certain position.Fusing all these methods together creates a multimodal emotion recognition system. The multimodal approach is a lot more dynamic but it has to correlate multiple types of inputs and finally integrate with probabilistic models.

Chapter 5

Research Challenge

EMG is an unexplored field while it comes to interacting with computers. That is why there are not many research paper published regarding this topic. But as it is a new and exciting area, many researchs are still ongoing to find different applications of EMG. We have found two research challenges regarding our findings:

- **Can EMG give better user experience than the traditional input devices while interacting with computer?** This area includes a couple of things. Firstly to find out the different applications or uses of EMG in human computer interaction. Secondly, this includes the comparison between the existing input devices with out proposed method. We tend to find out whether EMG can give better results or not.
- **Can our muslces convey human emotions to computer?** This is far more interesting and exciting question. Researchers have always tried to express our emotions to computers, because this is the barrier between a human and a machine. Machine cannot understand emotions yet. But if it can, then Artificial Intelligence will reach a new height. In this paper, we have tried to conduct an experiment with few users to see whether muscles convey emotions or not. [11] [2]

Chapter 6

Literature Review

We have studied papers related to emotion recognition through haptile mediums such as touch or users sitting positions, like arm movements and papers regarding Electromyography. As we have said before, sensing emotions with EMG or to use EMG as an input modality is an unexplored field. That is why there are not any papers related to emotion recognition with EMG. But studying similar papers, we are trying to analyze the subject.
The following section will include several paper reviews that we think closely matches our research area.

6.1 Papers Regarding EMG

6.1.1 Enabling Always-Available Input with Muscle-Computer Interfaces

Authors: T. Scott Saponas, Desney S. Tan, Dan Morris, Ravin Balakrishnan, Jim Turner, James A. Landay
Publication: Proceedings of the 22nd annual ACM symposium on User interface software and technology, Vancouver, BC, Canada, 2009
Problem Identification: Previous work has demonstrated the viability of applying offline analysis to interpret forearm electromyography (EMG) and classify finger gestures on a physical surface. As computing environments become more diverse, we often find ourselves in scenarios where we either cannot, or prefer not to, explicitly interact with a physical device in hand. In everyday use, if we are to use EMG data to interact with a computer, then we have to do it in real time. So We have to find a way to do so, and this paper proposes a solution to negate this problem.
Proposed Solution:

- They have presented a system that classifies these gestures in real-time and we introduce a bi-manual paradigm that enables use in interactive systems
- They have shown how forearm electromyography (EMG) can be used to detect and decode human muscular movement in real time, thus enabling interactive finger gesture interaction.
- They have explored techniques that will enable people to interact with computers when their hands are already being used in one of these grips, or when their hands are unencumbered but a handheld device is impractical.

Experiment Setup: They have divided the experiment into three parts:

- Part A: The first part of their experiment explored performing finger gestures when the hands were not holding anything. Each participant performed pinch gestures with the thumb and one of the other fingers of their dominant hand. The gestur ing arm was held in a comfortable position with a bent el bow and the empty hand held at about shoulder height
- Part B: The second part of their experiment explored performing finger gestures when the hands are already busy holding an object. As before, participants performed 25 blocks of finger ges tures in response to stimuli. The same stimuli highlighting fingers in the outline of a hand were used. Participants were asked to exert a little more pressure with the highlighted finger than with the other fingers.
- Part C: In addition to testing the accuracy with which their system was able classify gestures performed by participants, they also applied these gestures to use in a more ecologically valid application, a portable music player interface.

Results:

- Part A: The system performed best when clas sifying pinch gestures using training data that was gathered in the same posture. Furthermore, training transferred more effectively between postures that were more similar

- Part B: When participants held a travel mug in their hand, the four finger recognizer attained an average accuracy of 65% without visual feedback (see Figure 7). Mean classification improved dramatically, to 85%, with visual feedback

Advantages: The advantages of this research includes:

- Demonstrate that muscle sensing can be used to accurately classify a useful variety of finger gestures, even when the hands are under load
- Making forearm muscle sensing viable for human computer interaction
- It highlights the tradeoff between speed and accuracy that results from providing users with immediate visual feedback
- it introduces a novel bimanual technique for accurate engagement/disengagement of the recognizer, a crucial aspect of making muscle sensing usable for interactive tasks

Limitations:

- They have performed this experiment on a very few number of participants, although the number is enough to justify their research claim, but enough to create doubts
- Their device is wired, so participants had to stay at the lab table all the time. Whether their claim is accurate for a wireless device is yet to see
- The data set include much noise

Conclusion: This paper proves that EMG data can be used to accurately detect gestures, and if it can detect gestures accurately that means EMG gives valid data. This dataset can be further explored in other fields such as emotion.

6.1.2 Myopoint: Pointing and Clicking Using Forearm Mounted Electromyography and Inertial Motion Sensors

[5] **Authors:** Faizan Haque, Mathieu Nancel, Daniel Vogel
Publication: CHI 2015, Crossings, Seoul, Korea **Problem Identification:**

- Tracking hand and finger positions with enough fidelity in a large physical space across various environmental condi tions remains challenging.

- For example, Computer vision is susceptible to occlusion and lighting, and without additional markers, vision-based tracking of hands at arbitrary orienta tions over a large area is difficult

- An arm-mounted inertial measurement unit (IMU) provides motion and orientation tracking suitable for pointing with minimal environmental interference, but detecting a click re quires additional sensing. On-body computer vision is one approach [4], but inter-finger occlusion and lighting interfer ence remain problematic.

Proposed Solution:

- They describe a mid-air, barehand pointing and clicking inter action technique using electromyographic (EMG) and inertial measurement unit (IMU) input from a consumer armband de vice. The technique uses enhanced pointer feedback to con vey state, a custom pointer acceleration function tuned for an gular inertial motion, and correction and filtering techniques to minimize side-effects when combining EMG and IMU in put.

Experiment Setup: They had sets of a Transition Task followed by a Sequence Task. In both tasks, the current target was rendered as a blue circle on a black background and the next target rendered as a blue outline.

- Transition Task – This simulates transitioning to the pointing technique. After the cursor and target appear at controlled locations, the participant activates the technique and selects the target. The initial cursor position relative to the target is controlled. Note that Vogel and Balakrishnan use a synthetic activation technique, we use our real Myopoint activation.

- Sequence Task – This simulates continuous pointing usage. Immediately after selecting the transition target, the participant selects a sequence of 6 more targets at controlled distances and randomized directions. Participants had to successfully select each target before the next would appear. After the sequence task, the participant used the deactivation gesture to simulate a transition back to a non-pointing task.

Results:

- Some degradation in performance when moving from a Vi con to a consumer-level EMG and IMU armband is expected.
- Considering the Vicon as an ideal upper bound, Myopoint performance is quite good. Myopoint is slower for techni cal reasons: clicking with the hand spread posture is slower than small finger movements with AirTap, and despite their filtering, correction, and transfer function, very fast or careless clicks can still cause cursor jumps and participants were sometimes cautious. Further tuning may help.

Advantages:

- Their work demonstrates that distant pointing interaction is practical for consumer-level EMG and IMU sensing
- When we talk about electromyography, we think of expensive devices that are used for medical fields. But consumer level low cost EMG device can be used as an interactive medium is surely an important step in human computer interaction.

Limitations:

- They have only shown clicking and pointing functions but interactions are not limited to only that
- Whether myo armband can be used to navigate a whole interface is still unclear

6.1.3 Demonstrating the Feasibility of Using Forearm Electromyography for Muscle-Computer Interfaces

Authors: T. Scott Saponas, Desney S. Tan, Dan Morris, Ravin Balakrishnan
Publication: CHI Proceedings: Physiological Sensing for Input, Florence, Italy
Problem Identification:

- While transducers such as mouse, keyboard, touch sensitive devices have enabled powerful interaction para digms and leverage our human expertise in interacting with physical objects, they tether computation to a physical arti fact that has to be within reach of the user.

- To date, most efforts at enabling implement-free interaction have focused on speech and computer vision, both of which have made significant strides in recent years but remain prone to interference from environmental noise and require that the user make motions or sounds that can be sensed externally and by definition cannot be easily concealed from those around them.

Proposed Solution:

- They conducted an experiment to explore the potential of exploiting muscular sensing and processing technologies for muCIs(Muscle Computer Interfaces).

- They envisage that muCI sensors can essentially be worn on the body much like a watch or jewe lry, they provide an always-available and highly personalized input technology.

- The work presented in this paper is an initial step in explor ing how EMG technology can be used as an input modality

Experiment Setup: The high-level goal of their work is to determine whether muCIs are even feasible using EMG technology. We seek to employ EMG technology in such a way that muscle-computer interaction can be comfortable, unobtru sive, and useful for computer input.
Their approach is to place EMG sensors in a narrow band formation on the upper forearm. We envision this eventual ly becoming a thin wireless band worn just below the elbow.
Tasks: Participants performed four distinct sets of finger gestures. Each participant began each of the tasks with his hand in a relaxed palm-down position on the table, which we refer to as the rest position. For most participants, this meant that fingers were mostly extended, but slightly curled. We asked participants to return to this rest position between gestures.
Results: In classifying single samples, our Position classifier per

formed at an average accuracy of 71% (sd: 9.0%) while Pressure classified at about 76% (sd: 6.1%).

Advantages:

- This paper is one of the first step towards researching with Electromyography. So it tells us about the potential applications or uses of EMG in HCI
- This paper is proof that EMG can be accurately used to detect finger gestures, and thus opening a wide possibility for other human activity recognition

Limitations:

- One of the most significant limitations on their current clas sification results was the degree of inaccuracy in our labels when we trained and tested the gesture classifier

Chapter 7

Experimental Setup

We are going to define our proposed methodologies in two layers:

- Wearable Device to compare two interaction methods: traditional & EMG

- An experiment to classify human emotion through electromyography data

7.1 Apparatus

Our device includes the following components:

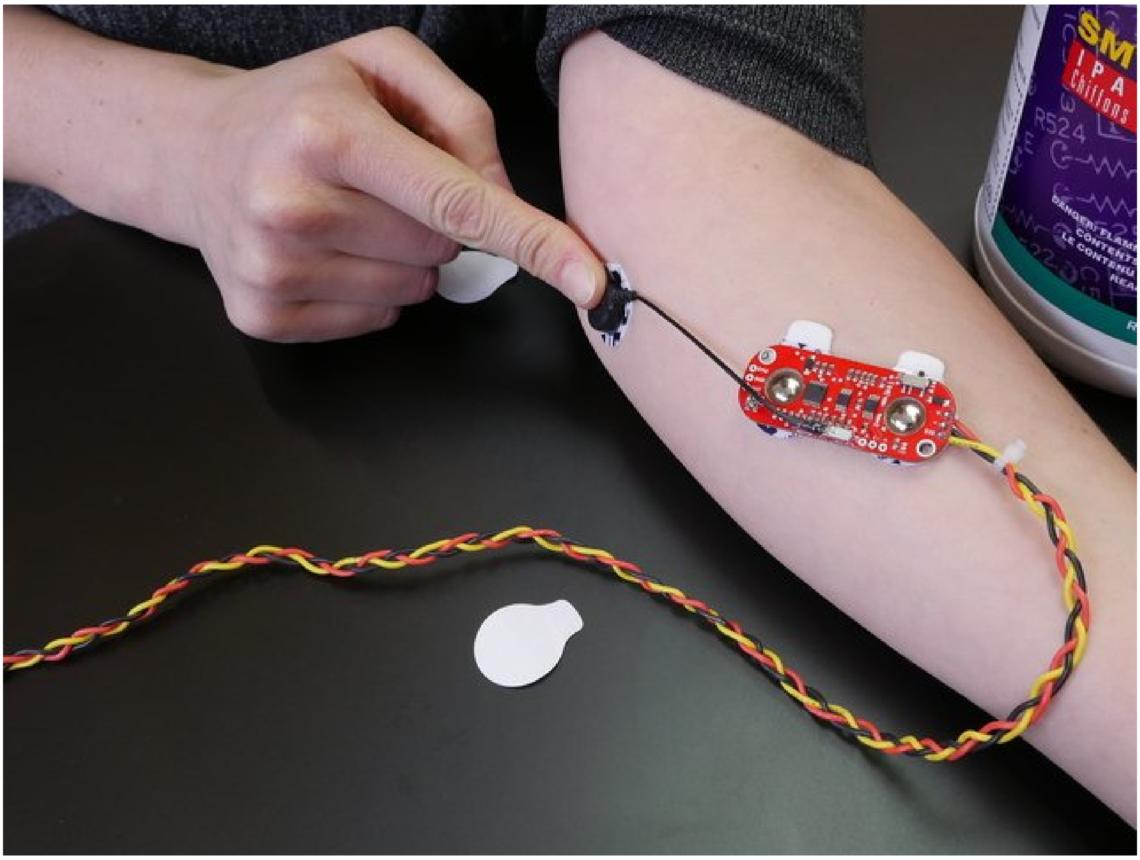
- MyoWare Muscle Sensor

- Arduino Mega 2560

- Electrode Pads

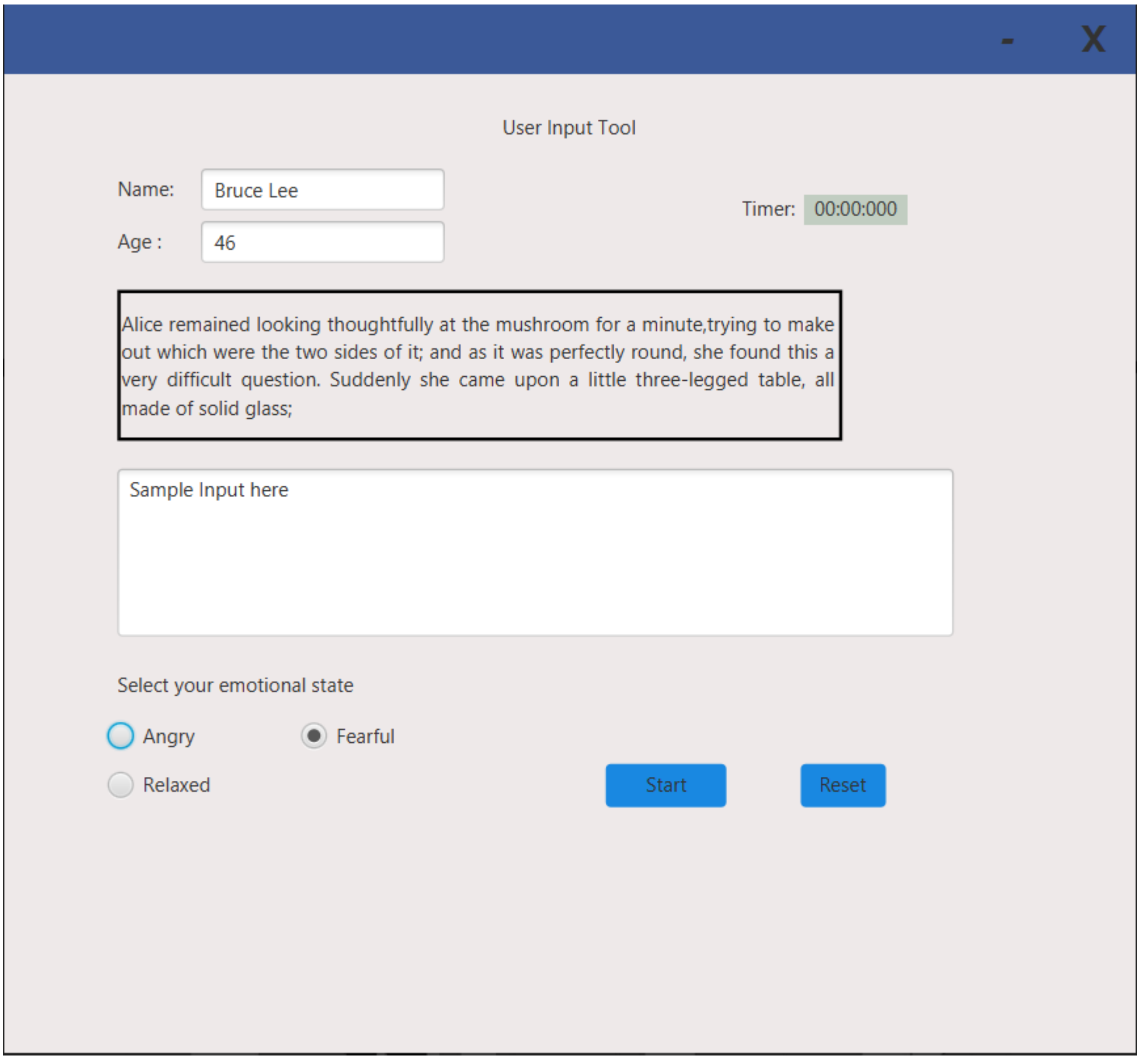
- Wires

We have used a low cost version of our muscle sensor, so that the research can be accessed by the majority. This device is worn on the forearm.



7.2 Experiment

We have selected 10 university going individuals consisting of both male and female as our users. The wearable device was placed on the forearm of the users dominating hand. The experiment followed two steps:
Firstly, in **"Fixed"** typing method, the users were told to type a certain paragraph exactly as it is in a **"Relaxed"** state. The users were shown pictures that induce relaxing features of ones mind. They listened to soothing music for about one minute. On the computer screen a paragraph was displayed taken from the famous children's novel *Alice's adventures in wonderland*(Carroll 2008)According to Epp et al.(2011)



The reasons behind choosing these text excerpts are that they have relatively simple sentence structure, an absence of large uncommon words and that each piece of text is roughly the same length. The raw data from the sensor along with the timing was recorded. The users were again told to type the passage but this time in a **"Angry"** emotional state. They were shown anger inducing picture on the computer screen. Finally they were told to type the passage in a **"Fearful"** state to conclude the fixed typing step.

In the **"Open"** typing stage, the users were told to type anything they want for one minute in Relaxed, Angry and Fearful emotional state consecutively. Again the raw sensor readings were recorded.

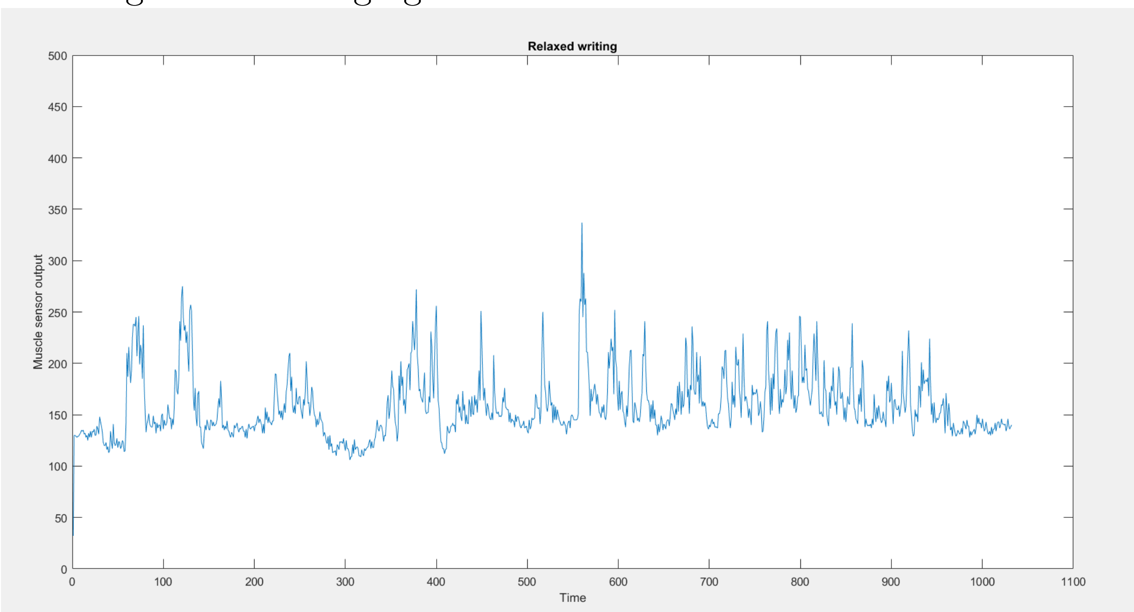
The reason for choosing this type of experimental setup is that, while typing, the muscles of forearm and fingers are most active and the responses can be accurately collected.

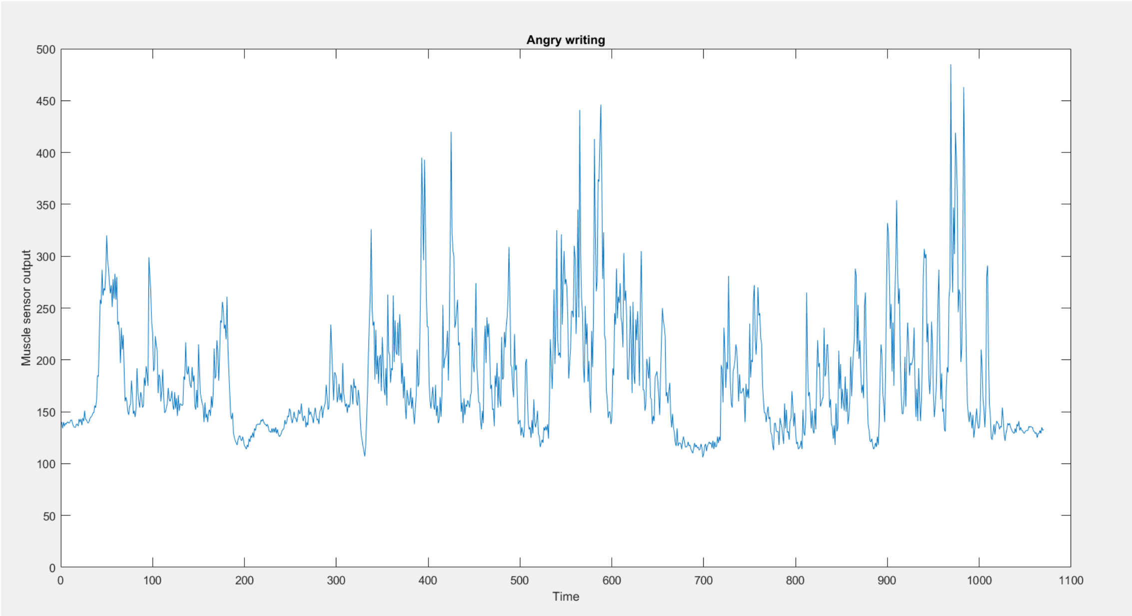
7.3 Filtering

The MyoWare sensor has some built in filtering mechanisms to reduce noise which makes it the ideal device to capture muscle data. In our experiment, we told the users to not type anything for the first 10 seconds and the last 5 seconds after they have done typing the paragraph. Our initial filtering process includes the reduction of those irrelevant data from the raw ones.
Apart from filtering some general normalization has been done. Data which were anomaly were eliminated.

7.4 Raw Data

The sensor readings were collected from the Arduino software and saved it into excel using the terraterm software. The sensor readings are integer values ranging from 0 to 999.




Angry writing
Muscle sensor output
Time
0
50
100
150
200
250
300
350
400
450
500
0
100
200
300
400
500
600
700
800
900
1000
1100

Chapter 8

Feature Extraction

From papers regarding feature extraction from EMG or EEG signal, it is understood that features are divided into two domains: [10]

- Time Domain
- Frequency Domain

But frequency domain features create redundancy while doing classification. So we have selected the following 8 features form time domain: [1]

- **Maximum Peak in a Timespan:** This means in a specific timespan what is the maximum peak of raw data
- **Mean Absolute Value:** Mean absolute value (MAV) is one of the most popular used in EMG signal analysis (e.g. Hudgins et al., 1993; Zardoshti-Kermani et al., 1995). It is similar to IEMG feature which is used as an onset index, especially in detection of the surface EMG signal for the prosthetic limb control. However, there are many given names for calling this feature; for instance, average rectified value (ARV), averaged absolute value (AAV), integral of absolute value (IAV), and the first order of v-Order features (V1). MAV feature is an average of absolute value of the EMG signal amplitude in a segment
- **Mean Absolute Value Slope:** Mean absolute value slope (MAVSLP) is a modified version of MAV feature to establish multiple features (e.g. Miller, 2008; Zecca et al., 2002). Differences between MAVs of the adjacent segments are determined. The equation can be defined as: where K is number of segments covering the EMG signal. When number of segments increases, it may improve representation of the original EMG signal over traditional

MAV feature. In study of Miller (2008), number of segments K is set to 3 that is also used in this study

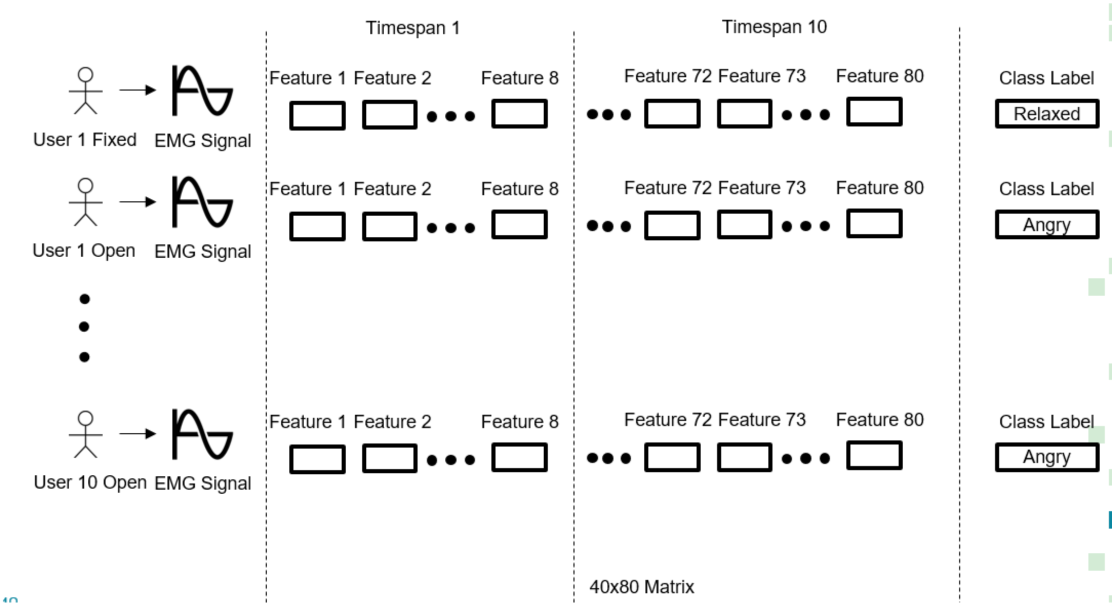
- **Picks Above Average Frequency:** This means how many peaks are there above the average frequency
- **Root Mean Square:** Root mean square (RMS) is another popular feature in analysis of the EMG signal (e.g. Boostani & Moradi, 2003; Kim et al., 2011). It is modeled as amplitude modulated Gaussian random process whose relates to constant force and non-fatiguing contraction. It is also similar to standard deviation method
- **Average Amplitude Change:** Average of how many times amplitudes change in a timespan signal
- **Difference Absolute Standard Deviation Value(DASDV):** Difference absolute standard deviation value (DASDV) is look like RMS feature, in other words, it is a standard deviation value of the wavelength (Kim et al., 2011),
- **Waveform Length:** Waveform length (WL) is a measure of complexity of the EMG signal (e.g. Hudgins et al., 1993; Oskoei & Hu, 2008). It is defined as cumulative length of the EMG waveform over the time segment. Some literatures called this feature as wavelength (WAVE).

Chapter 9

Classification

9.1 Training Data Generation

We have in total 10 users, from each user we have collected 4 types of data. They are: Fixed Relaxed, Fixed Angry, Open Relaxed, Open Angry. So there are 40 types of data or 40 ”rows” in the training data matrix. Then each data is divided into 10 timeslots. In each timeslots there are 8 features. So there are 80 features in total per row. In total the matrix size is 40x80. The process is described in the figure below:



The matrix looks like the following in MatLab:

40x80 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	197.5500	98.7770	167	207	197.8400	1008	3.6298	4.4381	196.9100	98.4530	174	206	197.2000	1076	3.8747	4.6868	265.7600	216.3500	133	440	276.3600
2	194.8800	97.4390	150	224	195.6600	1218	4.3593	5.0186	284.6300	142.3200	119	408	290.9000	1503	5.3794	7.3635	431.1100	347.4100	130	688	454.0300
3	224.3000	112.1500	110	271	224.9400	1117	3.9680	4.6760	237.2800	118.6400	132	297	238.3800	1209	4.2948	5.0315	243.3600	185.2800	140	276	243.9500
4	201.1900	100.5900	161	251	202.8000	1408	4.8468	13.1430	202.2100	101.1100	46	557	228.1700	1256	4.3236	6.6748	225.0500	166.5500	122	502	237.0600
5	181.7000	90.8490	152	202	182.2400	666	2.3559	2.9778	176.8300	88.4170	121	211	177.3400	977	3.4560	4.2578	229.7000	173.6600	144	268	230.7300
6	137.9200	68.9610	157	201	140.9700	852	2.0451	5.5579	132.2900	66.1470	171	189	134.5300	915	2.1964	3.0645	205.5300	175.2300	154	389	230.6600
7	181.7000	90.8490	152	202	182.2400	666	2.3559	2.9778	176.8300	88.4170	121	211	177.3400	977	3.4560	4.2578	229.7000	173.6600	144	268	230.7300
8	137.9200	68.9610	157	201	140.9700	852	2.0451	5.5579	132.2900	66.1470	171	189	134.5300	915	2.1964	3.0645	205.5300	175.2300	154	389	230.6600
9	197.5500	98.7770	167	207	197.8400	1008	3.6298	4.4381	196.9100	98.4530	174	206	197.2000	1076	3.8747	4.6868	265.7600	216.3500	133	440	276.3600
10	194.8800	97.4390	150	224	195.6600	1218	4.3593	5.0186	284.6300	142.3200	119	408	290.9000	1503	5.3794	7.3635	431.1100	347.4100	130	688	454.0300
11	219.2200	109.6100	139	235	219.3700	1773	6.6157	7.7501	233.4700	116.7400	144	258	233.7200	1761	6.5709	7.7766	250.0400	193.4300	140	340	252.0900
12	140.9900	70.4940	142	181	141.7900	715	2.5868	6.8486	287.4000	143.7000	105	621	345.5600	1340	4.8480	7.2995	207.8100	139.7200	106	390	222.9700
13	118.8700	59.4360	144	134	119.5500	430	1.5162	6.1348	113.8500	56.9230	115	130	114.1600	512	1.8054	2.2511	113.0100	83.8290	97	137	113.4100
14	179.1400	89.5700	121	194	179.3100	1148	4.1103	4.7001	176.8100	88.4050	142	191	176.9700	1092	3.9098	4.6517	189.3000	144.3400	80	246	190.2600
15	275.5400	137.7700	169	361	280.9800	1418	5.0499	6.3668	257.1100	128.5500	152	329	259.6200	1441	5.1318	6.1198	274.1600	203.8800	167	351	276.2800
16	211.2600	105.6300	120	271	212.6700	864	3.0094	3.7391	167.9300	83.9670	142	187	168.0900	628	2.1874	2.8230	175.2200	131.8600	137	199	175.4500
17	222.3200	111.1600	112	423	244.6700	916	2.8202	4.3254	153.0200	76.5120	186	206	157.3700	552	1.6995	2.2994	191.6000	143.5600	206	234	196.3200
18	149.7000	74.8510	128	168	150.2000	444	1.6093	2.0577	148.2600	74.1300	126	166	148.7100	580	2.1022	2.7281	154.2900	118.0900	97	185	155.0100
19	222.3200	111.1600	112	423	244.6700	916	2.8202	4.3254	153.0200	76.5120	186	206	157.3700	552	1.6995	2.2994	191.6000	143.5600	206	234	196.3200
20	149.7000	74.8510	128	168	150.2000	444	1.6093	2.0577	148.2600	74.1300	126	166	148.7100	580	2.1022	2.7281	154.2900	118.0900	97	185	155.0100
21	180.2600	90.1300	144	199	180.8800	1112	4.0643	11.4930	192.8800	96.4400	128	218	193.3500	759	2.7741	3.5145	305.4800	232.1900	187	343	307
22	136.2400	68.1190	122	149	136.5700	574	2.1833	2.5357	137.4900	68.7430	122	157	137.9100	593	2.2556	2.7848	242.4500	189.7100	155	326	250.3700
23	146.3600	73.1780	124	174	146.9100	449	1.6250	2.1266	129.1000	64.5510	126	146	129.3600	400	1.4477	1.7879	145.5000	114.2000	135	190	147.5500
24	156.1000	78.0490	140	181	156.9800	862	3.2188	10.7000	210.2000	105.1000	130	301	215.4200	1041	3.8872	4.8272	205.1100	156.6000	153	308	208.2100
25	240.9500	120.4800	128	377	245.3800	1380	4.7293	5.6776	226.5800	113.2900	157	277	228.2100	1172	4.0164	4.8271	208.5900	159.4200	135	267	210.9500
26	203.3600	101.6800	144	224	203.6400	789	2.7880	6.7737	210.7700	105.3900	116	247	211	810	2.8622	3.5937	251.3400	199.0800	87	394	259.4300

9.2 Classification Aprroach

There are two approaches to generate test and train data:

- **Leave One Out:** Here out of 10 users, 1 user was kept aside for test data and the rest 9 were used for train.
- **80-20 Method:** In this approach, 20% of data is selected as random for testing. The rest are training data

In our research we have followed both the techniques.

9.3 Algorithm

We have used Support Vector Machine with 5 folds cross validation to classify our dataset. Our class labels are "Relaxed" and "Angry". The kernel used is called "Radial Basis Function. The SVM algorithm picks up the best 5 features from the 80 feature and matches the features. **RBF:** The kernel function is a measure of similarity between two sets of features.

Command Window

```
Selected User for testing : 8
Start forward sequential feature selection:
Initial columns included:  none
Columns that can not be included:  none
Step 1, added column 38, criterion value 0.0833333
Step 2, added column 7, criterion value 0.0833333
Step 3, added column 31, criterion value 0.0833333
Step 4, added column 32, criterion value 0.0833333
Step 5, added column 39, criterion value 0.0833333
Final columns included:  7 31 32 38 39
ans =
     1     1
     1     1
     2     2
     2     2
test_accuracy_for_iter =
   100
Selected User for testing : 4
Start forward sequential feature selection:
Initial columns included:  none
Columns that can not be included:  none
Step 1, added column 38, criterion value 0.0277778
Step 2, added column 7, criterion value 0.0277778
Step 3, added column 31, criterion value 0.0277778
Step 4, added column 32, criterion value 0.0277778
Step 5, added column 39, criterion value 0.0277778
Final columns included:  7 31 32 38 39
ans =
     1     1
     1     1
     2     2
     2     2
```

```
Command Window
Start forward sequential feature selection:
Initial columns included:  none
Columns that can not be included:  none
Step 1, added column 44, criterion value 0.03125
Step 2, added column 47, criterion value 0.03125
Step 3, added column 48, criterion value 0.03125
Step 4, added column 55, criterion value 0.0625
Step 5, added column 1, criterion value 0.09375
Final columns included:  1 44 47 48 55
Row number | Predicted | Original |
        29 |         2 |        2 |
        16 |         1 |        1 |
        36 |         2 |        2 |
        17 |         1 |        1 |
        32 |         2 |        2 |
         9 |         1 |        1 |
        34 |         1 |        2 |
        33 |         2 |        2 |
test_accuracy_for_iter =
   87.5000
Start forward sequential feature selection:
Initial columns included:  none
Columns that can not be included:  none
Step 1, added column 21, criterion value 0.0625
Step 2, added column 19, criterion value 0.09375
Step 3, added column 31, criterion value 0.09375
Step 4, added column 47, criterion value 0.09375
Step 5, added column 48, criterion value 0.09375
Final columns included:  19 21 31 47 48
Row number | Predicted | Original |
        15 |         1 |        1 |
         7 |         1 |        1 |
```

9.4 Accuracy

Following the Leave One Out approach we got around 93% accuracy for 400 iterations. And following 80-20 approach we got around 88%

accuracy for 400 iterations.

9.5 Confusion Matrix

The confusion matrix for the leave one out method is as follows:

Original

Predicted

	Angry	Relaxed
Angry	777	88
Relaxed	23	712

The confusion matrix for the 80/20 method:

Original

Predicted

	Angry	Relaxed
Angry	1473	331
Relaxed	76	1320

Chapter 10

Future Works & Conclusions

10.1 Future Works

For our future studies we plan the following:

- Build a wireless version of our device
- Use machine learning approaches to classify emotions
- Build the interactive virtual table tennis application to conduct the experiment

10.2 Conclusion

In this paper, we tried to explore a field of interaction that has yet not been explored. We have tried to find out whether EMG could be a potential method to interact with a system and whether it can produce better results than the traditional methods or not. The results we found were satisfactory and can be used to prove that users have better user experience with our wearable device.

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