EVALUATING APPROPRIATENESS OF EMG AND FLEX SENSORS FOR CLASSIFYING HAND GESTURES

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Hand and arm gestures are a great way of communication when you don’t want to be heard, quieter and often more reliable than whispering into a radio mike. In recent years hand gesture identification became a major active area of research due its use in various applications. The objective of my work is to develop an integrated sensor system, which will enable tactical squads and SWAT teams to communicate when there is absence of a Line of Sight or in the presence of any obstacles. The gesture set involved in this work is the standardized hand signals for close range engagement operations used by military and SWAT teams. The gesture sets involved in this work are broadly divided into finger movements and arm movements. The core components of the integrated sensor system are: Surface EMG sensors, Flex sensors and accelerometers.

Surface EMG is the electrical activity produced by muscle contractions and measured by sensors directly attached to the skin. Bend Sensors use a piezo resistive material to detect the bend. The sensor output is determined by both the angle between the ends of the sensor as well as the flex radius. Accelerometers sense the dynamic acceleration and inclination in 3 directions simultaneously.

EMG sensors are placed on the upper and lower forearm and assist in the classification of the finger and wrist movements. Bend sensors are mounted on a glove that is worn on the hand. The sensors are located over the first knuckle of each figure and can determine if the finger is bent or not. An accelerometer is attached to the glove at the base of the wrist and determines the speed and direction of the arm movement. Classification algorithm SVM is used to classify the gestures.
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CHAPTER 1

INTRODUCTION

The project’s objective is to develop sensor system that allows soldiers to communicate and convey hand signals and gestures wirelessly to a heads up display in the absence of a line of sight.

Gestures, such as waving the hand or moving the leg, are commonly used in our daily lives. Gestures are often used as just a support for our verbal communication, but they can also be used as a sole, simple and effective way of communication. A primary goal of gesture recognition is to create a system which can identify specific gestures and use them to convey information or for device control. Gesture recognition is one of the important research topics in the field of computer science with the goal of interpreting human gestures through mathematical algorithms. Current trend of research include emotion recognition from the face and hand gesture recognition.

Gesture recognition can be seen as a way for computers and other processing units to understand human sign language and thus providing a more convenient way of interaction between computers and humans than the traditional interaction mechanisms like graphical user interface (GUI), which still dominate the world. Gesture recognition enables humans to interface with the computers directly without the need of any mechanical devices. This could make the input devices such as the mouse, keyboards and touch pads less redundant.

Gesture recognition is a way to understand human sign language, as well as there are many other types of uses:

- Special assistive robots: Using proper sensors like gyros and accelerometers and by reading the values from those sensors, robots can assist in patient rehabilitation.
• Game technology: Gestures can be used to interact with video games to try and make the players experience more real.

• Remote control: Through the use of gestures we can control various devices like remote control.

• Virtual controllers: For systems where the act of finding or acquiring a physical controller requiring much time, gestures can be used as an alternative control mechanism.

• Controlling through face gestures: Controlling a computer system through facial gestures is a useful application for people who may not physically be able to use a mouse or a keyboard.

Depending on the type of application, the approach for interpreting a gesture could be done in many different ways. The basic characteristic attributes for defining a gesture could be based on a 3-D model based, skeletal based model, appearance based model, raw signal attributes like EMG, EEG etc. data acquired from position measuring systems like gyros and accelerometers.

The controlling of external peripheral devices can be achieved by identifying the different motion commands from EMG signals. To achieve this, the pattern monikers for each type of motion command are extracted and proper mapping is applied to classify the signals. Nevertheless, the complexities in the EMG signal pattern makes it very difficult to have a precise structural and mathematical model that relates measured signals to motion command. There are many pattern recognition methods available to categorize the patterns extracted from different features. Using different classification methods like artificial neural networks, using machine-learning techniques like support vector machines (SVM) and logistic regressions, can do pattern
matching. Artificial neural networks especially became very popular among researchers in recent times.

Gesture recognition is a very useful utility in tactical and close range engagement situations where the soldiers have to act quickly and verbal communication is not possible especially when there is no line of sight (LOS) or when there are obstacles between the soldiers. Our work mainly involves classifying gestures used by the SWAT teams for CRE operations. Initial approach to classify these gestures was based on the idea that, whenever we perform a gesture an electrical potential is generated in the muscle groups present in the forearm. This electric potential generated in the muscles is called electromyography potential or simply as EMG. EMG sensors mainly act as an interface between human and computer systems used for human computer interaction (HCI) like mice, keyboards, joysticks etc.

Electromyography (EMG) is a technique that measures the electrical activity of the muscles at rest and during contraction. Nerve conduction studies measures how well and how fast the nerves can send electrical signals. The EMG signal is a biomedical signal, which represents the neuromuscular activities. EMG is a very complicated signal, which is controlled by the nervous system, which depends on the anatomical and physiological properties of the muscles.

Tendon forces play a major role in the design of tools and the most accurate approximation of tendon forces is necessary for a proper design of hand tools so that the users are not subject to harmful effects. Using electromyography is an effective tool to effectively calculate the tendon forces. Basically, the current (AC) that is generated due to muscle movements is called EMG. It is basically an electrical potential or voltage changing over time.
The raw EMG signal is an oscillating wave with an amplitude increase during muscle activation. Most of the energy content of this signal lies in the frequency range of 5 to 250 Hz.

A distinctive characteristic computed over the raw EMG signal for the diagnosis of muscle activity is windowed root mean square amplitude of the measured potential. The root mean square (RMS) value of EMG potentials is typically been used for diagnosis purposes such as evaluating the muscle functions during rehabilitation after a surgery or for assessing the muscle activation to assess gait. RMS amplitude is a rough metric for how active a muscle is at a given point in time. Apparently, as most of the EMG –based applications have originated for use in medial or clinical settings, some assumptions are made about the preparation and setup of EMG measurement devices, about the processing of EMG signals. EMG prototypes help in determining the position and pressure of finger presses and tapping and lifting gestures across all five fingers.

There are two kinds of EMG in wide spread use: surface EMG (SEMG) and intra muscular EMG (invasive EMG). To perform the intramuscular EMG a needle should be inserted through the skin into the muscle tissue. Invasive EMG is very accurate in sensing muscle activity but is generally considered to be impractical for human computer interaction applications. Invasive EMG is practiced by trained professionals (such as neurologists, physical therapist, chiropractor etc.). Invasive EMG provides valuable information about the state of the muscle and its nerves. Normal muscles at rest make some normal electrical signals when the needle is inserted into them. Abnormal spontaneous activity indicates some muscle damage or muscle activity. So these signals are measured and analyzed carefully to characterize the muscle activity or diagnose the muscle damage. Invasive EMG is considered too unnecessary in some cases. Instead we can use a surface electrode to monitor the general picture of muscle activation.
Surface EMG is fundamentally noisier than invasive EMG since the motor unit action potentials (MUAP) must pass through body tissues such as fat and skin before a sensor on the surface can capture them. Due to the high sensitivity of the EMG sensors required to detect these signals, they also detect other electrical phenomenon such as activity from other muscles, skin movement over muscles, electromagnetic radiations from electrical circuits and neighboring computer systems, environmental noise etc. This is used in a number of settings where: for example in a physiotherapy clinic etc.

Human computer interfaces (HCI) initially were implemented by direct manipulation of devices such as mice, keyboards, pens, dials, touch sensitive surfaces etc. Conversely, as computing and digital information became integrated into our every day environments it becomes too tedious to carry devices such as mice, keyboards so it becomes difficult or inconvenient to handle such input devices. For example, a driver querying the vehicle navigation system might find it very helpful when he use voice commands or can be able to do so by just moving his hands from the steering wheel. Another example is that a person in a meeting can use his /her hands to monitor a computing device without even disturbing the other persons.

The EMG sensors can be worn around the arm attached to an armband or a wristwatch or can be attached to the body. They can also be integrated into a nice body worn electromyography based controller where one or more sensors are integrated into an armband or a wristwatch. The sensor nodes measures the electrical activity in the muscles and the signals can be transmitted either wired or wirelessly to a computing system where the signals can be processed and analyzed. I used the off the shelf surface EMG components from I cube X systems to capture the surface EMG sensors.
Bio Flex is a signal-capturing device, which allows us to capture the EMG signals and convert them into the form suitable for use by computer for interactive applications. Generally surface EMG sensors are used to capture various EMG signals regarding the forearm movements. The prototype thus formed is then used to develop a numerical expression of the current muscle shape in the form of a series of data frames, which constitute various postures of
the muscle and associated EMG data. The set of EMG prototypes could be used to optimize the system accuracy.

The Bio Flex system is used to capture EMG signals for various postures of arm and leg. The device basically consists of a band carrying the sensors, called gold sensors, attached to the muscle in consideration. There is also a facility to adjust the tightness of the band, for effective correction of the EMG signals, by using the cambuckle. This Bio Flex band is attached to a Wi-micro Dig device to accept the EMG signals as input and show them as waves by converting them into the appropriate form. The com port is then selected and then the minimum and maximum settings are verified and then the patch is run. Now we can start trying a few hand gestures and postures and record the activity. For example, if the fingers are squeezed into a fist, a particular voltage is generated. As the fist is squeezed harder, the voltage generated rises. Care should be taken that the voltage generated should not exceed the input capacity of the input device.

The muscles contract to create a movement. The brain sends an electrical signal to the muscles to contract. This electric signal is sent to the motor neurons from the brain. The motor neurons and muscle fibers together are called motor units. There is a lot of voltage passing on between the muscle fibers and the motor neurons. The activity going on inside of a muscle unit is called motor unit action potential (MUAC). There are two sensors used to capture the MUAC signals. They are surface EMG and invasive EMG.

The invasive EMG is improper to use in practical situations and cannot be used to properly capture the signals because it involves needles to be inserted inside the skin to accurately record the voltages. The surface EMG though less accurate is currently used to record the voltages corresponding to various muscle movements.
We generate frequency energy for each sample recorded corresponding to the muscle movements. Frequency energy indicates the firing rate of muscle energy. The muscle energy and fatigue are the deciding factors in determining the frequency energy. To obtain the frequency energy, the following steps are followed. The fast fourier transform (FFT) of the obtained MUAC sample is performed. The frequency energy corresponding to each frequency is obtained. We also performed the cepstrum calculation of the raw MUAC samples. A cepstrum is the result of taking the Fourier transform of the logarithm of the spectrum of a signal. A MATLAB program has been developed to record the posture data from the hand motion and EMG signals from the muscle. The positional and orientation parameters are recorded. These two data are recorded in the form of a prototype for each muscle movement.

Many excellent EMG measurement devices are currently available but suffer some disadvantages due to insufficient number of channels, inadequate signal conditioning and inconvenient connectivity.

Pattern recognition is used to compare the EMG signals obtained with the prototype EMG signals. This comparison is used to determine the numerical representation of a hand shape or muscle shape. Three dimensional hand postures can be obtained from the pattern recognition performed either in time domain or frequency domain. There are many methods for sensing the EMG signals. Single sensing and multi-sensing are some of the different approaches that can be used to record the EMG signals. The factors affecting the EMG signal are:

- Causative factors: These are based on the physical equipment of the electronic equipment.
• Intermediate factors: These are the physical factors determined by the effect of one or more causative factors.

• Deterministic factors: These are the effects of intermediate factors and may include terms like motor firing rate and muscle interaction.

Some of the major types of noise affecting the EMG signals are:

• The inherent noise in the electrical equipment: Use of high quality electronic equipment is necessary to remove the noise contained in electrical equipment.

• Ambient noise: This noise arises due to electromagnetic radiation. We are constantly exposed to electromagnetic radiation on the earth and it is almost impossible to prevent such exposure.

• Motion artifact: Accurate design of electronic equipment is necessary to prevent the motion artifact that disturbs the data.

• Instability of signal: The firing ranges of motor units affect the EMG signal. The amplitude of EMG is random and cannot be certainly projected.

Sometimes it becomes very difficult to inherit important features from the underlying muscles of physical disabled people or form an amputee. This becomes more difficult when we are trying to classify a multi class problem.

The quality of EMG signal can be improved by using the following methods:

• The noise should always be minimum and the signal to noise ratio should be the highest.

• The distortion of EMG signal should be minimum and thus unnecessary filtering can be prevented.
Measurement of surface EMG signals depends on a number of factors and the amplitude of the surface EMG signals ranges from microvolts to the low millivolts range. The time and frequency domain properties of the SEMG signals and also the signal amplitude properties depend on factors such as:

- The timing and intensity of muscle contraction
- Distance of the electrode from the active muscle area
- Properties of over lying tissue
- Electrode properties
- Quality of contact between the electrode and the skin.

Placing the electrodes over the same skin location can minimize the variability in surface EMG recordings. Also in addition to that there are various other methods of normalizing the EMG signal to reduce the variability both within and between subjects.

Another type of sensor that is used to classify the gestures is the bend sensor or the flex sensor. These are the sensors that can change in resistance depending on the amount of bend in the sensor- the more the bend the more the resistance value. They are usually in the form of a very thin strip and their length usually varies from 1”-5” long.
CHAPTER 2
BACKGROUND AND RELATED WORK

2.1 Related Works

In recent years hand gesture identification became a major active area of research due its use in various applications. Surface electromyography (SEMG) though it is not that accurate as invasive electromyography (EMG), but still we used it to differentiate different gestures because it is simple and doesn’t require much efforts to record the EMG. Also SEMG gives pretty much optimum results while identifying different gestures. Amplitude and spectral information of EMG were used potentially as one of the features for supervised learning to train a classifier, which could classify different gestures.

There is a very near relation between RMS of SEMG and the finger flexion, suggesting that SEMG can be used for tele-operators and virtual reality entertainment (Reddy & Gupta 1996). SEMG is subjected to interference by various factors such as:

- Muscle anatomy (spatial distribution of motor units, number of active motor units)
- Physiology of the muscles
- Factors affecting nerves
- Level of contraction
- Interference caused by cross talk
- EMG recording sensors faults

The work proposed in this paper is motivated by the need for stronger classifiers to classify different gestures, although our area of work is not a relatively new concept to the research world. For some time now, the work to classify gestures based on EMG signals is going
on. Many researchers have done a good amount of work on EMG classification with reasonably good accuracy.

In SICE Annual Conference 2007 Kyung Wong Jung and Hyun Kwan Lee, 2 professors from Kagawa University Japan, proposed a method of pattern recognition of EMG signals of hand gestures using spectral estimation and neural network. Their proposed system consists of Yule-Walker algorithm to estimate the power spectral density and learning vector quantization (LVQ) to improve the accuracy of the classification.

T. Scott Saponas and Desney S. Tan did another previous work where they explored the concept of muscle unit computer interaction (MUCI). They conducted an experiment to exploit the potential of muscle sensing and processing technologies. They also demonstrated the experiment of differentiating gestures with an off the shelf electromyography device.

Yusu, Mark H. Fisher and David. J Burn who proposed a method of using EMG potentials generated during hand and muscle movements to control an artificial prosthetic hand worn by an amputee. Surface EMG sensors were used to record SEMG potentials and using a novel 3D electromagnetic positioning system to with a data glove having 11 sensors. The prototypes thus generated are stored and then compared with the acquired EMG Frames the most likely data frame is identified and then used to control a robotic hand.

Artificial neural networks have been used to classify the different EMG signal patterns to classify the gestures. At the 2011, 4th INTERNATIONAL CONFERENCE ON MECHATRONICS in May 2011 at Kuala Lumpur the team of Md Rezwanul Ahsan, Muhammad Ibn Ibrahimi, Othman O Khalifa presented a paper on classifying EMG signal based hand gesture recognition using Artificial neural networks. Different EMG pattern signatures are
extracted from the signals for each movement and then artificial neural networks are used to classify the EMG signals based on features.

Similar work can be found in the United States Patent Number US 8,170,656 B2 filed by the Microsoft Corporation. They designed the wearable electromyography based controller, which includes a multitude of electromyography sensors and provide a wired or wireless interface with computing systems and attached devices via electrical signals generated by the precise movements of the user’s muscles. Trailing the initial automated self-calibration and positional localization processes, measurement and interpretation of the muscle generated signals is accomplished by sampling of the muscle generated electrical signals by the EMG sensors of the wearable electromyography based controller.

The user into a coarsely approximate position puts on the wearable electromyography unit on the surface of the user’s skin. Automated instructions are provided to the user for fine-tuning the placement of the wearable electromyography based controller. An armband is used as a wearable electromyography based controller.

The wearable electromyography based controller described above is a unique device for measuring user muscle electrical activity for interaction with other devices following an automated position localization process for self selecting a set of appropriate sensor nodes to capture the electrical activity of particular gestures.

The wearable electromyography based controller operates by first attaching the sensor nodes of the controller to the user’s skin. The sensor nodes are provided either as individual sensor nodes or as a set or group of sensor nodes, such as on an armband, wristwatch etc. Once the user has worn the wearable electromyography based controller, a self-calibration module operates in cooperation with a training module to associate the electrical signal, which is
generated by particular muscle groups in response to a particular gesture or motion of the user in various embodiments. In some embodiments the user is instructed or given some training, directing the user to perform some gestures to assist the training module and self calibration module in learning the various signals generated by the users motion. In some examples, the user is provided with a feedback module to direct the user in repositioning the wearable electromyography based controller so as to better position the sensor nodes to capture particular EMG signals.

The initial calibration process is not described in much detail in this patented as the patent application is still pending. In various examples, the calibration is done either periodically or on a need basis for the changes in muscle activity as the result of movement of the sensor nodes during use. After the initial calibration process, a positional localization module starts operating to estimate the positions of the sensor nodes on the users body and also the positions of the sensor nodes to the other sensor node groups. During this process the user feedback module may operate to direct the user to reposition the sensor nodes to capture better signals.

After the position localization process, the wearable electromyography based controller is used to capture the electrical signals generated by user’s muscles. Some additional features may be implemented in order to improve the clarity of captured signals. For example a multiplexing module can be implemented to improve the clarity of the signal by determining which sensor nodes should be used to capture the electrical signals generated by muscles.

A power control module is used to power down or disable the sensor nodes that are not being used, which are determined by the multiplexing module. These are generally used for wireless controllers, which particularly have the power limitation. Then the signal capture module receives the signal generated by the muscles captured by the active sensor units of the
wearable electromyography based controller. A control module, which acts as an interface between the computer systems, interprets the captured electrical EMG signals and electromyography based controller. So this control module provides human computer interaction (HCI) for monitoring, controlling and interacting with one or more computing devices. Once the electrical signals are interpreted the control module just acts like any other HCI such as mouse, keyboard etc.

Figure 2.1: Setup and use of the wearable electromyography-based controller
Finally the wearable electromyography based controller operates on the electrical signals generated by the muscles; a control feedback module exists to provide feedback to the user so that the user can know which particular command has been entered. The control feedback module operates to provide a haptic, visual or audio feedback to the user that a command has been successfully entered or executed in response to electrical signals generated by muscles resulting from gestures. Haptic feedback can be a vibrating device in the controller, a visual feedback can be lights in the controller and audio feedback can be playing a voice.

Table 2.1: Difference between Implementations

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<th>Our Proposed Implementation of the Gesture Recognition System</th>
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<td>Sensor nodes are integrated into an armband or a wristwatch and are worn at approximate positions on the body.</td>
<td>Surface EMG sensors are attached to a strap and are worn at fixed predetermined position on the forearm.</td>
</tr>
<tr>
<td>Self-calibration module operates to associate muscle generated electrical signals with specific gestures.</td>
<td>We use a fixed gesture set involving hand and arm signals of soldiers and tactical squads in close range engagement operations (CRE).</td>
</tr>
<tr>
<td>Position Localization Module operates to determine body position and relative position of sensor nodes.</td>
<td>The position of the sensor nodes is fixed with three surface EMG sensors attached on the top of the forearm to capture the electrical signals of the extensor movements and two sensors attached to the bottom of the forearm to capture the flexion movements.</td>
</tr>
<tr>
<td>On board multiplexing module operates to determine which sensor nodes to use.</td>
<td>There is no multiplexing module in our system with all the 5 channels of the EMG system are used for capturing the signals.</td>
</tr>
<tr>
<td>Power control module is used to switch on and switch off the battery in case of idle state.</td>
<td>We are not implementing a power control module as such but we are considering this to implement this in our future research.</td>
</tr>
<tr>
<td>A user-training module is implemented to direct the user to perform specific gestures.</td>
<td>Before we classify the gestures of a particular user we take some sample gestures of the user to build a database of the user’s samples before comparing the new sample of the user with the existing database of samples.</td>
</tr>
<tr>
<td>A control feedback module operates to provide visual or audio or haptic feedback to the user. I am not sure about the classification algorithms followed by the Microsoft, as it is not given in the patent.</td>
<td>The feedback module is not implemented in the current research but will be implemented in the future research. We are pretty sure that we follow a different approach to what they follow because we use machine-learning algorithm like support vector machines to classify the gestures.</td>
</tr>
</tbody>
</table>
A team of Ukrainian students called Quad Squad developed gloves that can translate sign language into speech. The project is entitled as Enable Talk that is presented at the Microsoft’s Imagine Cup in Sydney. There are about 40 million people in this world who are deaf and deaf-mute those who communicate only with sign language. As there are only few people who can understand sign language, so the Enable Talk team has built a system that can translate sign language into text and then into spoken words using a text-to-speech engine. The whole system then connects to a smartphone over Bluetooth. The team has built a number of prototypes and tested them with sign-language users in Ukraine.

The different parts of the controller are:

- **Main controller:** The controller is the main element of the system and its task is to analyze signals from sensors and transmit the data result to a mobile device.
- **Accelerometer/compass:** It is a system-in-package featuring a 3D digital linear acceleration sensor and a 3D digital magnetic sensor.
- **Accelerometer/gyroscope**
- **Accelerometer/oscilloscope:** It is a system-in-package featuring a 3D digital accelerometer and a 3D digital gyroscope.
- **Micro controller:** They used the Atmel AVR XMEGA A3, which is a family of low power, high performance and peripheral rich CMOS 8/16-bit microcontroller.
- **Bluetooth module**
- **Flex-sensor:** They used the flex sensors, which are of 2.2” and 4.5” in length. As the sensor is flexed the resistance across the sensor increases. Resistance changes depending on the amount of bend in the sensor.
2.2 Anatomy of the Forearm

The forearm is the structure and region of the upper limb between the elbow and the wrist. The forearm contains two long bones, the radius and ulna forming the radio ulnar joint.

The forearm or antebrachium contains many more muscles than the arm. These muscles are responsible for the movement of the forearm, wrist and the digits. The muscles fall into two groups – a flexor/pronator group and extensor/supinator group. The flexor group occupies the anterior compartment of the forearm. This group of muscles arises from or in line with the medial epicondyle of the humerus. The extensor group of muscles occupies the posterior compartment of the forearm. This group of muscles from or in line with the lateral epicondyle of the humerus.
2.2.1 Anterior Muscles of the Forearm

The muscles responsible for flexion of the digits are:

- Flexor digitorium superficialis
- Flexor digitorium profundus
- Flexor pollicis longus

2.2.2 Posterior Muscles of the Forearm

The muscles that extend the middle 4 digits are:

- Extensor digitorium
The muscles responsible for extension of the thumb are:

- Abductor pollicis longus
- Extensor pollicis brevis
- Extensor pollicis longus

Figure 2.4: Anterior and posterior muscles of the forearm
2.3 Gesture Set

Hand and arm gestures are a great way of communication when you don’t want to be heard, quieter and often more reliable than whispering into a radio mike. We should have a standardized set for our cell.

When on the move, we should shoot an eye towards cell members every ten or fifteen seconds in case they are trying to signal us. Get in the habit of passing the hand signals on.

In this project we used the standardized hand signals for close range engagement operations used by military and SWAT teams. The gesture sets involved in the experiment are broadly divided into finger movements and arm movements. The number gestures include lifting one finger, two fingers, three fingers and so on.

Some of the close range hand signals are: line abreast formation, wedge formation, files formation, column formation, sniper, hostage, and enemy.
Figure 2.5: Hand and arm gestures for close range engagement (CRE) operations
<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Enemy</strong></td>
<td><strong>Hostage</strong></td>
<td><strong>Sniper</strong></td>
<td><strong>Dog</strong></td>
<td><strong>Cell Leader</strong></td>
</tr>
<tr>
<td><strong>Column Formation</strong></td>
<td><strong>File Formation</strong></td>
<td><strong>Line Abreast Formation</strong></td>
<td><strong>Wedge Formation</strong></td>
<td><strong>Rally Point</strong></td>
</tr>
<tr>
<td><strong>Pistol</strong></td>
<td><strong>Rifle</strong></td>
<td><strong>Shotgun</strong></td>
<td><strong>Ammunition</strong></td>
<td><strong>Vehicle</strong></td>
</tr>
</tbody>
</table>

Figure 2.6: More hand gestures
<table>
<thead>
<tr>
<th>Gesture</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>I Understand</td>
<td></td>
</tr>
<tr>
<td>I Don't Understand</td>
<td></td>
</tr>
<tr>
<td>Crouch or Go Prone</td>
<td></td>
</tr>
<tr>
<td>Breach(e)</td>
<td></td>
</tr>
<tr>
<td>Gas</td>
<td></td>
</tr>
<tr>
<td>Door</td>
<td></td>
</tr>
<tr>
<td>Window</td>
<td></td>
</tr>
<tr>
<td>Point of Entry</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2.7: More hand gestures
CHAPTER 3

CORE COMPONENTS OF THE PROTOTYPE

3.1 Bio Flex Sensors

The Bio Flex sensor band is designed with a 40 cm elastic band intended to hold the sensor module in position on the arm or leg. The sensor module has 3 gold sensor contacts that are designed to contact the skin and capture the underlying electromyography (EMG) electrical signals from underlying muscles.

- Sensor contact adjustment: The gold sensor contacts works for most people with simple skin contact. The skin should be very clean and free of any oily substances. Some users with very dry skin can get better bio flex operation by putting a little tap water on the skin, then dry off the excess water and then applying the sensor band. The band includes a 1m cable with a connector that plugs into the Wi-micro Dig unit. The Wi-micro Dig unit is worn at a distance from the sensor band and allows the freedom of motion of arms and legs.

- Use of Bio Flex: The sensor band has a cambuckle, which can be used to adjust the fit of the band around the arm. The simplest way to put on the band is to first slip the tongue of the elastic band into the cambuckle, then slide the loose band onto the arm and tighten the elastic band when the band is in the desired position and then latch the cambuckle closed.

![Figure 3.1: Bio Flex EMG Sensor](image)
3.1.1 Bio Flex Usage

To start using the Bio Flex position the band such that the gold sensor contacts the inside surface of our forearm. By using the I Cube X editor:

- Launch the Bio Flex Max patch
- Plug the Bio Flex into the Wi-micro Dig
- Connect the Wi-micro Dig battery
- Red LED flashes

With the Bio Flex screen in view we select the input com port. Then we wait for few seconds for the Blue tooth connection to be established with the system. A blue light appears on the Wi-micro Dig. Next we verify the min and max sliders are set to 0 and 511 respectively.

3.1.2 Proper EMG Sensor Placement

Proper placement of EMG sensors on the forearm muscles is necessary to obtain noise free quality surface electromyography (SEMG) signals. Improper placement of SEMG sensors on forearm muscle groups leads to distorted EMG signals due to noise in EMG readings generated by cross talk signals in the surrounding muscles.

Some of the guidelines to be followed for the location of the EMG sensors as given in:

- The sensors have to be placed along the longitudinal direction of the desired muscle fibers.
- The sensors should not be placed on the outside edge of the muscles, as in this region the sensors are susceptible to cross talk signals from the surrounding muscles.
- The sensors should be placed between a motor point and the tendon insertion or between any of the two motor points.
• The sensors should not be placed on or anywhere near the motor units. The motor units are an area in the muscle such that an introduction of even a small amount of electrical current in those units can cause a recognizable amount of jerk in the surface muscle fibers. These motor units are areas with greatest neural density. This is a poor area for sensor placement because the signal propagates in multiple directions and it is difficult to measure.

• The sensors should not be placed near the tendons because the muscle fibers near the tendons are thinner and do not produce signals of higher amplitude. Also the sensor placement is quite difficult because the muscle fiber is physically smaller.

3.2 Wi-micro Dig

The Wi-micro Dig is a thumb sized hardware device that encodes analog voltage signals generated by sensors to industry compliant MIDI messages. It transmits these messages wirelessly to our computer using serial port of Bluetooth.

The communication protocol used by the Wi-micro Dig is based on MIDI protocol. The communication protocol used by the Wi-micro Dig is I-Cube X Wi-micro Dig communication protocol version 6.1. The MIDI implementation number is same as the firmware version number and can be obtained by send a DUMP VERSION command to the Wi-micro Dig.

There are 3 different working modes for Wi-micro Dig:

• General mode

• Standalone mode

• Host mode
The Wi-micro Dig MIDI implementation uses the following message format for all system exclusive messages:

<table>
<thead>
<tr>
<th>Byte</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>240(F0H)</td>
<td>System Exclusive Status</td>
</tr>
<tr>
<td>125(7DH)</td>
<td>Manufacturer ID</td>
</tr>
<tr>
<td>{DEV}</td>
<td>Device ID</td>
</tr>
<tr>
<td>{CMD}</td>
<td>Command or Message ID</td>
</tr>
<tr>
<td>{BODY}</td>
<td>Main Data</td>
</tr>
<tr>
<td>247(F7h)</td>
<td>End of System Exclusive</td>
</tr>
</tbody>
</table>

### 3.3 Flex Sensors

Flex sensors are the sensors that change resistance depending on the amount of bend in the sensors. They convert the change in bend to electrical resistance so that the more the bend the more is the resistance value. They are usually in the form of a thin strip from 1”-5” long, that vary in resistance. They also can be made unidirectional or bi-directional bend sensors depending on the application.

Their typical sizes are:

- 1 kilo ohm to 20 kilo ohm
- 20 kilo ohm to 50 kilo ohm
- 50 kilo ohm to 200 kilo ohm

#### 3.3.1 Working of the Flex Sensors

The Flex sensors are analog resistors. They work as variable analog voltage dividers. The Flex sensors have carbon resistive elements inside them within a thin flexible substrate. So this implies that if a Flex sensor has more carbon means it has less resistance and vice versa. Less
resistance typically implies it has less resistance range. When the substrate is bend the sensor produces a resistance output relative to the bend radius.

**Technical specifications**

<table>
<thead>
<tr>
<th>Product</th>
<th>BendShort sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Version</td>
<td>2.0 (2009)</td>
</tr>
<tr>
<td>Sensing parameter</td>
<td>flex angle multiplied by flex radius</td>
</tr>
<tr>
<td>Sensing method</td>
<td>piezo-resistive</td>
</tr>
<tr>
<td>Range</td>
<td>-180° to +180° (larger flex angle possible)</td>
</tr>
<tr>
<td>Active area</td>
<td>61 x 1.7 mm (2.4 x 0.67 inch)</td>
</tr>
<tr>
<td>Minimum flex radius</td>
<td>5 mm (0.2 inch)</td>
</tr>
<tr>
<td>Output impedance</td>
<td>13 KOhm (at 0° flex angle) to 150 KOhm (at 180° flex angle)</td>
</tr>
<tr>
<td>Calibration (using minimum flex radius)</td>
<td></td>
</tr>
<tr>
<td>Degrees</td>
<td>Voltage (use 5 V power supply) 7-bit MIDI value (use 'no processing' editor preset)</td>
</tr>
<tr>
<td>-180°</td>
<td>0.07 2</td>
</tr>
<tr>
<td>0</td>
<td>2.47 63</td>
</tr>
<tr>
<td>+180°</td>
<td>4.84 118</td>
</tr>
<tr>
<td>Power supply</td>
<td>1.0 to 10 V DC, 0.1 mA at 5 V</td>
</tr>
<tr>
<td>Sensor dimensions</td>
<td>96 x 6.0 x 0.1 mm (3.8 x 0.24 x 0.004 inch)</td>
</tr>
<tr>
<td>Weight</td>
<td>9 g (0.3 oz), incl. cable</td>
</tr>
<tr>
<td>Cable</td>
<td>1.0 m (39 inch); shielded, red wire = power, black wire = ground, white wire = sensor output, maximum extension 30 m (98 ft)</td>
</tr>
<tr>
<td>Connector</td>
<td>Male plug with a row of 3 pins spaced 2.54 mm (0.100 inch)</td>
</tr>
<tr>
<td>Application notes</td>
<td>The sensor output is determined by both the angle between the ends of the sensor as well as the flex radius; bending the sensor sharply will result in a more value change than bending the sensor smoothly, when keeping the ends in the same position. Shorter versions available as BendMicro and BendMini</td>
</tr>
</tbody>
</table>

Figure 3.2: Technical specifications of bend sensors

Infusion Systems manufacture the flex sensors in different sizes and can be chosen based on the type of application we deal with. There are 3 types of flex sensors manufactured from Infusion Systems:
• Bend short
• Bend micro
• Bend mini

Figure 3.3: Flex sensors
CHAPTER 4

ANALYSIS AND EVALUATION

Our working environment in the lab includes a MAC machine with MAC OSX Version 10.7.3 installed in it. The programming interface, which was used in our lab, was MATLAB R2011a edition. We assumed that the surface electromyography (SEMG) is the most suitable and convenient core component of the prototype as it is user friendly and very easy to measure.

In the first prototype built for the experiment we used off the shelf components from I-Cube X. The off the shelf components are the Bio Flex sensors. One sensor was attached to the upper forearm and the second was attached to the lower forearm just below the elbow. The sensors are placed in such a fashion that they are perpendicular to the muscle. The muscle running in the upper forearm is the Extensor digitorium upon which the sensor 1 (channel 1) is placed, the muscle running in the lower part of the forearm is the Flexor digitorium upon which the sensor 2 (channel 2) is placed.

The Wi-micro dig is connected to the MAC machine via the Bluetooth interface. The raw Bio Flex data from the Wi-micro Dig, which is transferred wirelessly to the MAC machine, arrives at the serial port. The serial port follows the traditional RS-232 standard.

A serial port is a physical interface through which the information transfers through it one bit at a time. The serial port is created via the MATLAB interface. The default serial port for the Bio flex sensors is the tty.I-CubeXWi-microDig0311. Before establishing communication with the Wi-micro Dig the Bio Flex sensors should be reset to NULL and the digitizer should be set to the host mode.
The default sampling interval for the Bio flex sensors is 100ms. However, the sampling interval can be adjusted to as low as 1ms which is the optimum sampling interval for EMG. In our case we chose 1ms as the optimal sampling interval for capturing EMG signals.

The default input and output buffer size of the MAC PC is set to 1 KB. However, the buffers size can be increased or decreased depending on our need.

In order to start the data capturing of EMG signals:

- Sensors have to be reset to Null
- Wi-micro Dig has to be set into host mode.
- Sampling interval has to be set

Writing into the serial port using the “fwrite” system call can do all these operations. Then we have to stream the sensors one by one so that their combined data is pumped into the input buffer of the system. After once streaming starts the gestures are performed whose data is recorded in the EMG signals by a sudden increase or decrease in the amplitude levels, which can be seen easily if we plot the acquired data in MATLAB with peaks in the graph.

The overall project setup can be divided into different phases.

4.1 Time and Fourier Domain Analysis

The purpose of this project is to classify different hand gestures used by the counter terrorist and SWAT teams. In the operation scenario the soldiers may or may not have a direct line of sight (LOS). So we are proposing to develop a system with different sensors such as EMG sensors, accelerometers, gyros etc. attached to the soldiers hands and then when the soldiers make a gesture that gesture is transmitted wirelessly using bluetooth to a heads up display (HUD) mounted on the soldier’s head. If a soldier makes a gesture that gets displayed on his
HUD and simultaneously it gets transmitted to other soldiers HUD, so that the other soldiers can get to know the gesture and act accordingly. If the sensors detect a wrong gesture then there is a feedback mechanism so that the soldier does the gesture once again. This is the whole setup of the project.

In order to work with the EMG sensors we did an extensive research on the different types of EMG sensors available in the market. We found out that there are several types of off the shelf EMG sensors, which are available at optimum costs and can sample at best possible sampling rates. Finally we decided to buy the sensors from Infusion Systems. The off the shelf components are the Bio Flex EMG Sensors. Initially we designed a two-channel EMG system, which can detect the electrical impulses from the muscles in the form of an analog signal, the Wi-micro Dig then samples the analog signal and the resultant digital signal is then transmitted to the computer wirelessly using bluetooth.

Some of the lessons learned are:

- We succeeded in developing an interface to receive EMG signals and analyze them using MATLAB.
- The various muscles in the cross section of the upper forearm all produce electrical voltages when finger gestures are performed so the cross talk between various muscles impaired localization.
- The various signal attributes found are: Raw EMG values sampled at 1000Hz and their N time discrete fast fourier transforms (FFT).

As the raw time domain signals are sampled at 1000 samples per sec, the highest frequency captured by the Wi-micro Dig is 500 Hz.
Figure 4.1: Raw time domain plots of two channels EMG system. X axis – Time (milli-seconds), Y axis- Amplitude( milli-volts)
The Fourier transform is a mathematical transform, which expresses a function of time as a function of frequency, or it transforms a function in time domain to a function in frequency
domain. The inverse Fourier transform, transforms a function in frequency domain to a function time domain. Basically there are two types of Fourier transform:

- Continuous Fourier transform
- Discrete Fourier transform

The continuous Fourier transform converts a time-domain signal of infinite duration into a continuous spectrum composed of an infinite number of sinusoids. Generally for dealing with analysis of signals in computers we deal with signals that are discretely sampled, usually at constant intervals and of finite duration. So for such signals Discrete Fourier transform (DFT) is appropriate. The result of DFT of an N-point input time series is an N-point frequency spectrum.

4.2 Cepstrum Analysis

The data collected from the two-channel EMG sensor system is not sufficient to achieve very high classification accuracies because of the limitations imposed by the surface EMG sensors. The signal features extracted from the raw time signal are the most basic features. The surface electromyography sensor system is redesigned with the addition of one more EMG sensor and also includes new feature extractions such as the Cepstrum.

The classification results using the two channels EMG sensor system made way for further research about the current state of the art EMG hand sensors available. Also, an in-depth study of different feasible implementations and solutions to the project was done. Initially we built a two-channel EMG sensor system with one sensor placed on top of the Flexor carpi radialis, which runs in the upper forearm and the second one was placed on the Flexor carpi ulnaris, which runs in the lower forearm. The classification is performed by taking samples of all the ten figure gestures namely from 1 to 10. Then the total sample set is divided into two sets,
named as training set to build a training matrix and the other set is named as test set to build a testing matrix. A training matrix is built using the samples from the training set and the corresponding rows of the training matrix are labeled using the class labels of the gestures. The class labels of the gestures are labeled as 1 to 10. The class labels are placed in a column matrix with the number of rows equal to the number of rows in the training matrix. Each sample is placed in a row in the training matrix. In a similar way test matrix and test labels are created.

LIBSVM is integrated software, which supports vector classification, regression and distribution estimation. It also supports multi class classification. LIBSVM is used for classification of the samples. The training matrix and the training label are given as inputs to LIBSVM to create a training model. Then the model is used to predict the labels of the samples in the testing matrix. The two-channel EMG sensor system produced very low classification results. So the sensor system was reconfigured to increase it from two-channel to three-channel.

Two sensors were placed on the upper forearm and one sensor was placed on the lower forearm. The sensors were divided into primary and secondary sensors. The sensor, which collects the best signal from the top, is selected as the primary sensor and the sensor at the bottom is taken as the secondary sensor. The signal analysis was done in 3 domains: time domain, frequency domain and cepstral domain.

Time domain is the raw time signals sampled at 1000 samples/sec. Frequency domain analysis is done by taking the fast fourier transforms (FFT) of the signals in the time domain. A cepstrum is obtained by taking the Fourier transform of the logarithm of the estimated spectrum of the signal. Cepstrum coefficients are widely used in speech recognition, generally combined with a perceptual auditory scale. Cepstrum can be seen as information about rate of change in
different spectrum bands. It has been used to determine the fundamental frequency of human speech and analyze radar signals.

Figure 4.3 shows the plots of the two-channel signal plots in the time domain, frequency domain and the cepstrum for gesture 1. A cepstrum is basically used to separate two or more signals from a mixture. The cepstrum plot in figure 4.3 for Gesture 1 and the cepstrum plots of all the other gestures have similar waveforms making it difficult to extract patterns from waveforms. This similarity in waveforms is due to the crosstalk between different muscle pairs, which impaired localization of the sensor nodes. The Bio Flex sensors have circular gold sensor plates with large surface area so the signals captured by these sensors contain lot of noise, which becomes very difficult to separate these signals from the noise.

Other machine learning techniques like Neural networks and Logistic regressions were also used to see weather they can produce better classification results of these samples, than the support vector machines. Neural network functions can be found in the neural network toolbox of MATLAB. In a similar way there are many different types of regression functions provided in MATLAB toolboxes. Out of the three classification techniques, support vector machine gave the best classification results.

Some of the lessons learnt are:

- Clinical EMG sensors were found to be much more accurate.
- The understanding gained from these sensors as well as further research into EMG allowed us to modify and reconfigure the I-Cube X sensors to an acceptable level of accuracy.
- Signal features extracted are: raw time domain signal, FFT, cepstrum
Some new classification techniques were identified such as: logistic regression, support vector machines (SVM), neural networks.

Figure 4.3: Finger gesture 1 two-channel signals plots with cepstrum. Upper portion shows the Time, Frequency and Cepstral domain plots of channel 1. Lower portion shows the Time, Frequency and Cepstral domain plots of channel 2.
4.3 Different Classification Techniques

4.3.1 Logistic Regression

Logistic regression is a type of regression analysis, which is used for prediction of the outcome of a categorical variable (variable limited to finite number of categories) based on one or more predictor variables. The logistic regression gives the probability distribution of the different outcomes of a particular random trial or random variable. The probabilities are modeled as a function of explanatory variable, using a logistic function.

Logistic regression measures the relationship between the categorical dependent variable and several independent variables by converting the dependent variable to probability scores. Logistic regression can be binomial or multinomial. Binomial means it has only two possible outcomes whereas a multinomial has many number of outcomes.

4.3.2 Support Vector Machine (SVM)

Support vector machines are supervised learning models with associated learning algorithms that analyze the training data, identify patterns in it and form a model, which is used to predict the category of a new testing set, which is encompassed. The basic SVM takes a set of input data and predicts which of the two groups the input belongs to. This is a basic non-probabilistic binary linear classifier. The SVM constructs a hyper plane in higher dimensional space. The input vectors are mapped onto this higher finite dimensional space. The hyper plane is selected such that the input there is a maximal difference between the support vectors of the two classes and the hyper plane.
4.3.3 Neural Networks (NN)

Generally we deal with the artificial neural networks. They are composed of interconnecting artificial neurons. The artificial neural networks are responsible for solving artificial intelligence problems. Artificial neural networks algorithms attempt to extract the complexity in the neural network and focus on what may hypothetically matter most for information. The basic architecture consists of 3 types of neuron layers: input layer, hidden and output. In some types of feed forward networks, the signal flow is from input to output strictly in a feed forward direction. The data processing can be extended to many layers but there is no feedback. Some recurrent networks contain feed back connections.

The classification results of the EMG samples taken from three-channel electromyography sensor system using LIBSVM, regression and neural network algorithms produced better classification results but still there is considerable amount of noise in the signals, which is hiding the important features of the original signal.

A better-reconfigured and optimized sensing system was developed with more specific sensor placements. Different sensor location combinations were tested all along the forearm to determine the best location for sensor placement to capture maximum signal quality. The part of the forearm right below the elbow has the maximum signal quality. Analysis on the anatomy of the forearm revealed that the muscles in the top of the forearm are responsible for extension of the fingers and the muscles running in the lower forearm are responsible for bending or flexion of the fingers.

A total of 5 EMG sensors were attached to a wearable cambuckle in such a way that 3 sensors captured the electrical activity of the muscles running in the upper forearm and 2 sensors captured the electrical activity in the muscles running in the lower forearm. The sensors were
attached in parallel to each other in the direction of the muscles flow to capture the signals with best quality. Out of the threes sensors attached on the top of the forearm the sensor which captured the best signal with minimum amount of noise is selected as the primary sensor. In a similar way the sensor, which captured the best signal, among the bottom group of the sensors is selected as the secondary sensor. This prototype was constructed with new optimized and 1.3-advanced version of Bio Flex sensors. Some of the most important tasks accomplished are:

- Using the optimized Bio Flex sensors, a new collection prototype was created using 3 to 5 sensors.
- Using support vector machines several revolutions of increased accuracy.
- Limiting the number of features to abstract and percentage based fast fourier transform (FFT) components, 70-75% classification has been achieved.

4.4 Five-Channel Analysis

The five-channel electromyography (EMG) sensors system was the best prototype built so far by using which the best-achieved classification accuracy till date was 75% using the samples of the finger gestures for training and testing purposes. To go further into the analysis five gestures were selected among the ten figure gestures such that, the gestures selected are as wide as possible with regard to the finger combinations used to make the gestures. The subset selection was to determine the narrowly distributed frequency bandwidths, which can be used for more precise classification of these gestures.
Figure 4.4: 5-channel raw time domain plots.
X axis- Time (milli seconds), Y axis- Amplitude (milli volts)
The gesture subset consists of the following 5 gestures:

- Gesture 1
- Gesture 3
Fresh round of samples were taken for each of the five gestures involving three normal and perfectly healthy subjects. Each subject took 50 samples for each of the five gestures. On the whole each gesture has 150 samples. Each sample was broken down into two groups: data from upper forearm group of sensors and the data from lower forearm group of sensors. The primary and the secondary sensors were selected for each sample. The five-channel data was merely broken down to a two-channel data with the selection of best sensors data from the two groups. After the selection of the primary and the secondary sensors the Fourier Transform of these samples were calculated using the fast fourier transform (FFT) algorithm in MATLAB to convert the data in time domain to the frequency domain. The Fourier data for each of the five gestures were placed in separate data matrices. Mean, variance and standard deviations were calculated at each frequency for each gesture. The mean, variance and standard deviation of each frequency were plotted for each gesture separately.

From the analysis of the plots of the mean, variance and standard deviations of each gesture separately, it was found that all of them have one common feature. The samples were found to be very randomly distributed from their means in other words they have very high variances and standard deviations. This analysis implies that every person has their own unique gesture performing styles and also it is very difficult to get synchronization among the subjects about the intensity with which a gesture is performed. One assumption from this analysis is that the samples of the individual subjects would have very narrow distribution from their respective means. To prove the assumption the samples of just one subject were taken and similar analysis
was performed. The plots showed very low variances and standard deviations. So to improve the classification accuracy the five-channel prototype has to be calibrated from subject to subject before classification.

To determine the dominant frequency bandwidths of each gesture the difference between the samples of every combination of gesture pairs were calculated. Before taking the differences each sample was normalized to even out the variations in the samples, and to make each sample uniform. It was found that each gesture has higher amplitude spikes compared to the other gestures in a very narrow frequency bandwidth of 1-1.5 Hz. These bandwidths are very narrowly distributed in the range of 33-44 Hz.

Probability distribution tables are constructed using the dominant frequency bands of each gesture. The contents of the probability distribution tables are as follows:

- Columns of the tables consist of the dominant frequency bands for each gesture.
- Rows consists of multiple thresholds defined. A threshold is defined as the difference between the amplitude values of two gestures.
- Elements of the table consists of the probability estimation or percentage estimation of the number of different sample combinations which have a difference equal to the threshold value between the gesture pair.

Hence, all tables were constructed in a similar way. A new sample is taken and tested against these tables to estimate the probability contribution if each gesture to the sample. Whichever has the highest contribution or the highest probability then the sample is determined to belong to that gesture. So many test matrices were created by taking multiple samples and tested against these tables. The overall test results yielded on an average around 70-75%
In addition to support vector machines other supervised machine learning algorithms Naïve Bayes and K – nearest neighbors were also used to test these samples. MATLAB provides inbuilt functions for both the Naïve Bayes and K-nearest neighbors classification. The Naïve Bayes classifiers are based on so-called Bayes theorem and are particularly suited when the dimensionality of the input is very high. A Naïve Bayes classifier assigns a new observation to the most probable class, assuming the features are conditionally independent given the class value. The K-nearest neighbor is a method for classifying objects based on the closest training examples in the feature space. It is a type of instance-based learning where the function is only approximated locally and all computation is postponed until classification.

The results were much similar to the support vector machine (SVM) classification but LIBSVM computes at a much fastest pace among.

4.5 Wavelet Analysis

Wavelet analysis is a mathematical means to perform signal analysis when signal frequency varies over time. For certain class of signals wavelets analysis provides some precise information about signal data than other signal analysis techniques. Wavelet analysis can be performed in MATLAB or using the Wavelet toolbox. The toolbox contains many Wavelet transforms such as discrete, continuous, stationary wavelet transforms etc. Discrete wavelet transforms are used in this EMG signal analysis to dig much deeper into the signals to extract more non-recognizable signal features.

In signal, functional and numerical analyses, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. A key aspect in the preference
of Wavelet transforms over Fourier Transforms is that, the Wavelet transforms have temporal resolution: it captures both frequency and location information.

Figure 4.6: Average of 50 Samples of gesture 1 of primary sensor. X axis- Frequency (Hertz), Y axis- Difference (milli volts)
Figure 4.7: Average of 50 Samples of gesture 3 of primary sensor. X axis- Frequency (Hertz), Y axis- Difference (milli volts)
Figure 4.8: Variance, mean & standard deviation of gesture 1.
Blue- Variance, Red- Mean, Green- Standard Deviation.
X axis- Frequency (Hertz), Y axis- Difference (milli volts)
Figure 4.9: Variance, mean and standard deviation of gesture 3.
Blue- variance, Red- Mean, Green- Standard deviation.
X axis- Frequency (Hertz), Y axis- Difference (milli volts)

The basis for the wavelet transforms is called wavelets. A wavelet is a wave like oscillation function, with amplitude starting at zero, increases and then decreases back to zero. Translating and scaling a wavelet function known as the mother wavelet obtain the wavelet coefficients. Different types of mother wavelets are:
• Haar wavelet
• Daubechies
• Symlet
• Shannon

MATLAB is provided with a wavelet GUI using that we can work with the wavelets seemingly much easier than entering the wavelet commands from the Command line of MATLAB. Wavelets can denoise a signal in the time domain producing a much cleaner signal. The raw time signals were taken; first they were denoised to produce a much cleaner signal. Then the signal values of the primary sensor were taken from each sample. A 1-D discrete wavelet transforms were calculated using Haar, Daubechies and Symlet mother wavelets at level 4 to see which wavelet produces the best decomposition of the signal into approximation and detail coefficients. The ‘db’ wavelet produced a better decomposition of the signals than the other two wavelets.

The signal decomposition is done for each of the five Gesture Samples. We found that the signal features which are present in the detail coefficients and approximation coefficients of the respective signals are much the same for every gesture with slightly different waveforms for each gesture.

EMG is not good enough alone for the classification of the complete gesture set because:
• Finger gestures used by SWAT teams involves more than one muscle group of the lower forearm therefore it becomes difficult to identify which specific muscle groups are responsible for the creation of the individual gestures.
• The surface gold plated sensor nodes of the Bio flex device have large surface area so affixing these sensor nodes on specific muscle groups over the skin becomes difficult. So there is considerable amount of white noise in the signals.

Electromyography can be used to classify one, three, five, nine and fist gestures with an average accuracy of around 75%. In order to classify more gestures in addition to EMG sensors additional sensor types such as Flex Sensors were used.

4.6 Flex Sensors Analysis

The best achieved accuracy for the classification of the finger gestures of the standardized hand signals for close range engagement operations used by the military and swat teams using the EMG sensor affixed to the upper and lower parts of the forearm is approximately 75%. These gestures have higher voltage components in the frequency spectrum compared to the other gestures in narrowly distributed frequency bands such that it becomes very difficult to attain much higher classification accuracies. But still we can clearly distinguish the wrist movements to a much higher accuracy using EMG sensors.

So we decided to use other sensor types to classify the finger gestures to a much higher accuracy. The other sensor types used are the flex sensors or the bend sensors. These sensors as afore mentioned in the document when bent increases the resistance across the ends of the carbon element embedded in a thin substrate. This resistance can be converted to an electrical voltage when connected to a voltage divider circuit. These bend sensors use a piezo-resistive method of detecting the bend. The piezo-resistive method describes the change in electrical resistivity of a semiconductor when a mechanical stress is applied. The sensor output is determined by both the angle between the ends of the sensors and the flex radius. Bend sensors
are attached to a glove that is worn on the hand. The sensors are located over the first knuckle of each finger and can determine if the finger is bent partially, fully or straight.

Figure 4.10: Flex sensors mounted on a glove

To classify the gestures using the flex sensors there’s no need of any specialized machine learning algorithms like support vector machines, neural networks or Naïve Bayes algorithm etc. but a simple logical function like a Boolean function is sufficient enough to correctly classify gestures. If flex sensor is bent then we can assign a variable to 1 otherwise we can assign it to 0. Depending on the gesture type there can be different combinations of 1s and 0s, which can be used to accurately classify the gestures. Based on this idea we designed a simple custom algorithm for the classification purpose.
To obtain the best readings from the flex sensor the sensors have to be bent sharply around a radius of curvature rather than bending smoothly. So we attached the edge of the flex sensors to the first knuckle and then inserted into a neatly stitched cloth on the finger extension part of the glove so that they can be bent sharply and neatly around a radius of curvature when the figure is bent. The custom algorithm is based on a thresholding based classification.

The algorithm functions in the following way:

- The algorithm goes in and looks into each and every point of each flex sensor values in a sample and then checks if a point has value of less than 25 then it assigns a 0 otherwise it is assigned a value of –50. So the value of 25 is decided as the threshold for the flex sensor values.

- Then a moving average is calculated for each and every flex sensor values of the sample using a window of size 10. If the average value is less than some negative number like -1 then a Boolean variable is defined and is set to 1 otherwise it is set to 0. In other words if the flex sensor is bent the Boolean variable is assigned 1 if it is straight it is assigned 0. Same way for each flex sensor a Boolean variable is assigned.

- Depending on the Boolean values combination the particular gesture is displayed as the output.
Figure 4.11: Flex sensor plots
4.7 Conclusions

Electromyography can be used to classify “Dog”, “Stop”, “One”, ‘Five” and “Ten” gestures effectively with high degree of accuracy. The surface area of the sensor nodes is large compared to the slim muscle specific unobtrusive EMG sensors so there is considerable amount
of cross talk between the muscles, so the noise captured in the signals cannot be separated. So these EMG sensors cannot be able to classify more gesture types. The flex sensors offer a broader perspective. They are able to classify the whole of the finger gestures from one to ten 95% accurately.
CHAPTER 5

FUTURE WORK

We are currently researching the integration of new sensors into a full that achieves the maximum possible accuracy. We are working on the integration of the Accelerometers to estimate the position of the hand and to develop a 3D mapping system to graphically represent the hand position. An accelerometer is an electro mechanical device, which measures the acceleration of a device. The acceleration forces may be static like the constant force of gravity or they could be dynamic – which is caused by movement or vibration of the accelerometer. The accelerometers measure the amount of static acceleration due to gravity and thus we can find out the angle at which the device is tilted with respect to the earth. By sensing the amount of dynamic acceleration, we can analyze the way in which the device is moving. GForce3D senses dynamic acceleration and inclination (static acceleration due to gravity) in three directions simultaneously.

- It can be used for hand motion, jolt, jerk and impact detection as well as balance measurement.
- We can use it to measure the whole body expression; we can use the bend sensors or the flex sensors to capture all our joint movements. A Gforce3-D firmly attached on our feet and Bio flex EMG sensors to capture the muscle power gives the orientation of the feet a well as intensity with which the feet moves.
- We can attach it to the moving objects to measure their motion dynamics.

A custom encryption algorithm for safe transmission of the information to the HUD is also on the cards.
Figure 5.1: GForce3-D accelerometer
**Technical specifications**

<table>
<thead>
<tr>
<th>Product</th>
<th>GForce3D-3 sensor</th>
</tr>
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<tbody>
<tr>
<td>Version</td>
<td>1.1 (January 2008)</td>
</tr>
<tr>
<td>Sensing parameter</td>
<td>triaxial acceleration/deceleration</td>
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<tr>
<td>Sensing method</td>
<td>MEMS</td>
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<tr>
<td>Acceleration range</td>
<td>± 3 G</td>
</tr>
<tr>
<td>Acceleration resolution</td>
<td>18 mG (outputs 1 and 2), 28 mG (output 3)</td>
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</tbody>
</table>

**Acceleration calibration (output: 1, 2 or 3)**

<table>
<thead>
<tr>
<th>Acceleration (G)</th>
<th>Voltage (use 5 V power supply)</th>
<th>7-bit MIDI value (use 'no processing' editor preset)</th>
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</thead>
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<tr>
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<tr>
<td>+3</td>
<td>2.66</td>
<td>68</td>
</tr>
</tbody>
</table>

**Acceleration application notes**

With the pins of the connector facing yourself and the red power wire facing up, the rightmost pin is output 1, the center pin is output 2 and the leftmost pin is output 3. See drawing below.

**Inclination range**

-180° to +180°

**Inclination calibration (output: 1, 2 or 3)**

<table>
<thead>
<tr>
<th>Inclination (°)</th>
<th>Voltage (use 5 V power supply)</th>
<th>7-bit MIDI value (use 'no processing' editor preset)</th>
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<tr>
<td>+90</td>
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<td>50</td>
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</tbody>
</table>

**Inclination application notes**

Motion other than rotation (as a result of inclination or tilt) in any of the three sensitive axes may generate sensor output corresponding to the acceleration of the motor, see acceleration application notes.

**Bandwidth**

500 Hz

**Power supply**

3.5 to 15 V DC, 0.9 mA

**Operating temperature**

-25° to 70° C (-13° to 158° F)

**Sensor dimensions**

12 x 23 x 10 mm (0.47 x 0.81 x 0.40 inch)

**Weight**

25 g (0.8 oz), incl. cable

**Cable**

1.0 m (39 inch), shielded, red wire = power, thick black wire = ground, thin black wire = sensor output 1, white wire = sensor output 2, grey wire = sensor output 3, maximum extension 25 m (82 ft)

**Connector**

male plug with 5 pins in 3 rows spaced 2.54 mm (0.100 inch)

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Figure 5.2: Technical specifications of GForce3-D
BIBLIOGRAPHY


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Hasan, MR, Ibrahimy, MI, and Khalifa, OO. “Electromyography Signal based hand gesture recognition using Artificial Neural Network”


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