INSTITUTO TECNOLÓGICO Y DE ESTUDIOS SUPERIORES DE MONTERREY
CAMPUS MONTERREY
SCHOOL OF ENGINEERING AND INFORMATION TECHNOLOGIES
GRADUATE PROGRAM

TECNOLÓGICO DE MONTERREY®

EMG MONITORING SYSTEM USING FAST FOURIER TRANSFORM AND A FUZZY LOGIC CLASSIFIER

THESIS

PRESENTED AS PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE IN AUTOMATION

BY:
ESTEBAN JOSÉ SALAZAR CAMACHO

MONTERREY, N.L. DECEMBER 2011

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Esteban José Salazar Camacho

T h e s i s

Presented to the Graduate Program in Engineering and Information Technologies

This thesis is a partial requirement for the degree of

Master of Science in Automation

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Abstract

This thesis presents the design of an EMG (Electromyographic) signal monitoring system that senses the human hand. This system classifies the hand fingers motion and sends an output signal that can be used for a motion controller.

The myoelectric signals arise from the contraction or relaxation of a muscle. The EMG signals can be used as an input for a control system using a communication interface supported with electronic devices in order to perform the human machine interaction.

The sensors and the myoelectric signal acquisition used in this work are commercially available superficial electrodes, while the fuzzy logic algorithms and signal processing systems are developed in this thesis.

The acquisition system designed is able to amplify the input EMG and then a filter procedure eliminates the parasite and instrumentation noises, allowing the monitoring system to interpret the signal pattern and respond to the user motion.

This thesis is based in fuzzy logic to design a motion classifier. The goal of this work is to map the EMG signals generated from three human fingers, namely: index, middle and thumb motions, the proposed system can be integrated in an automated device that uses EMG as controlling signals.

Dedicatory

A mis padres y hermanos

Por su esfuerzo constante y apoyo

para lograr mis sueños en la vida,

Cada uno a su manera.

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Chapter 1
Introduction

The human body possesses great abilities that allow us to perform a wide range of activities. Focusing on the body motion, this is comprised by the muscle response of a bio-signal originated in the brain that contains the information of a specific task in a body limb. This thesis is intended to be the starting point of a series of studies in reproducing bio signals using mechanical devices that performs the motion of the human hand and forearm. The goal for this thesis is to acquire the EMG signal using an electronic interface, then a decision making process using a classifier provides the current input motion to an output signal that can be used further to control an automated hand prosthesis.

1.1. Statement of the Problem

There are many applications derived from electromyography signal analysis. This investigation considers the applications that involve technological development, and particularly those that can be used for biomedical prosthesis devices. Consequently, the following investigation questions are formulated.

- How is comprised the hand motion mapping?
- How is the classification of motion and grasping intensity?
- How the electromyography signals can be analyzed?
  - Which is the best method to process the electromyography signals?
  - How is constructed the electronic device for EMG signal processing?

Once the statement of the problem has been introduced, some characteristics that make this myoelectric virtual prosthesis simulator an innovative work, and contribute with actual studies that refer EMG signals are presented. Unfortunately, every year in Mexico, hundreds of people suffer different kinds of disease or accidents that results in the amputation of upper or lower limbs, disabling the person for the performance of some human motor system capacities. More specific is the case of several patients that suffered an amputation of hand or wrist as the only medical solution to stop disease propagation to other limbs.

Statistics provided from Xoco's Public Hospital in México City show that the number of cases of amputation surgery is over 43 per month, caused by various diseases [9]. Due to this fact is important to find new methods that provide with these patients the possibility of developing the lost abilities and hence improve their life quality. In the United States of America almost 1.7 million people have lost any extremity. It is estimated that one of each 200 persons in the USA have suffered an amputation caused by congenital diseases, cancer, traumatism or vascular diseases as is shown in Figure 1. Note that upper limbs referred to as arm, wrist and hand, while down limbs are legs and foot [13].

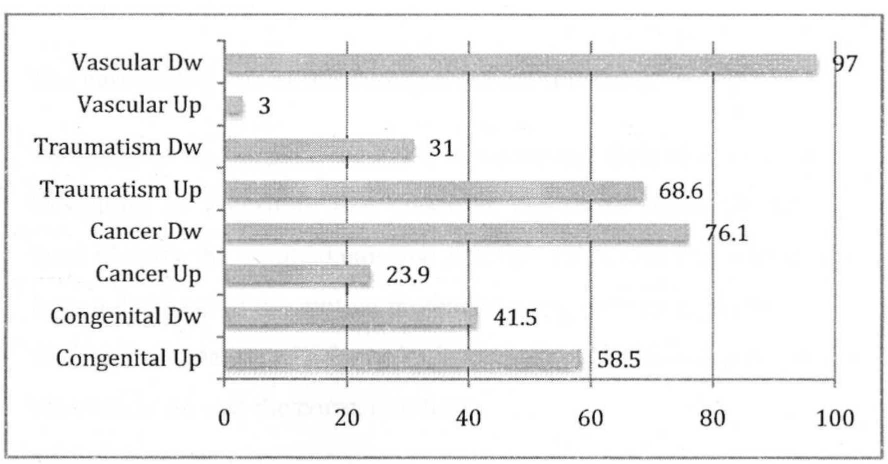

Figure 1. Medline statistics for each 100,000 discharge related with down (Dw) and upper (Up) limbs amputee in USA between 1988-1996 [13].

Thomson Reuters Health published additional information about cases of amputation, related with types of diabetes showing that in recent years the cases have diminish from 7 per each thousand to 4-5 per each thousand. Also the American Diabetes Association informed that about 65,000 patients with upper or down limb amputation in 2006 [14].

1.2. Aim of this Thesis

1.2.1. General Aim

This work is performed in order to map the EMG signals behavior of a human hand, for the implementation of a motion classifier that will be able to identify the characteristics of the signals from the fingers motion and provide the an output signal that can be used for controlling.

Hence the hypothesis of this work is to understand how taking advantage of the features of EMG signals to classify the hand fingers motion.

1.2.2. Particular Aim

The particular goals of this research are the following:

- To introduce and explain the EMG behavior and their characteristics.
- Designing an algorithm that classifies the EMG signal characteristics, this must identify the input signals and intensity to choose the most similar pattern from a database of the motion pretended using spectral analysis.
- The implementation of a fuzzy logic classifier algorithm capable of distinguish between noise and the correct motions.

After having defined the particular aims of this thesis that summarizes this research, the justification is defined.

1.3. Justification

Some of the inconveniences faced by a person disability that requires a prosthesis are: (i) to choose the most appropriate prosthesis to the user needs, (ii) the process of learning the device behavior and finally (iii) the assimilation of the prosthesis for daily life.

The main function of the monitoring system developed in this thesis is to propose an alternative of monitoring system that maps the three finger motions from a single channel and provide an output signal for a dynamic prosthesis which is composed of three degrees of freedoms, and uses a physiological response as a signal for controlling. EMG monitoring systems use one channel for a single muscle, which means that for three degrees of freedom, three channels are needed, which increase instrumentation, processing and costs.

The configuration proposed in this allows the user to manipulate the 3 degrees of freedom essentials index, middle and thumb motions to perform basic tasks using a reduced and low cost interface.

Human hand can perform a wide range of activities, each finger contributes with a certain level of motion and the whole system can perform the job. Each finger contributes for grabbing, pulling, hold, etc, but the main fingers to perform these jobs are index, middle and thumb motions, where ring and pinkie can be considered as secondary degrees of freedom. Based on this a

This research is the basis of a robotic system that uses EMG signals to control, propose a rehabilitation tool for patients and it is possible to use the same methodology to expand this system to other human body limbs as arm and legs where EMG signals are present. Furthermore, this system can be implemented in other areas as aerospace industry for the development of robotic arms, building industry with the design of exoskeletons as support, ergonomics, among others.

1.4. Possible Applications

There are two prosthesis types: dynamics and statics; whose are collocated in the nearest limb of the disabling area, each manufacturer develops different characteristics in their prosthesis, such as: degrees of freedom, battery duration, and others that will aid the users. Regretfully, most of dynamic prosthesis are expensive, starting on $25,000 dollars [9], and also many patients would never feels comfortable with prosthesis behavior, for different reasons. One is that manufacturers uses additional muscles for motion as for instance for moving an index finger, it is necessary to perform the motion using a muscle not related with the desired limb motion and this confusing training makes the user feels uncomfortable. For the statics, even if they are cheaper than myoelectric dynamics, it costs starts on $4,000 dollars, they present a low level of technology and the range of motions that user is able to perform is limited.

These precedents demonstrate the necessity of a new way of familiarizing with the robotic hand or wrist prosthesis behavior for next prosthesis users, a group of learning exercises nearest as possible as the real motions, and allow them to explode all benefits and limitations that the robotic limb provides. With technology advances these prosthesis will develop abilities almost the same as human anatomy structure.

The robotic prosthesis that replaces the lost body limb will use the electromyography signals (EMG) to recreate the previous motor system motions. Thus are detected using sensors or electrodes that can be located in the skin surface or in the inside. The EMG's are automatic signals that human brain emits and they owns electrical characteristics as frequency and amplitude, those can be used as control signals for myoelectric prosthesis, also they represent one of the most important electric control variable that are used in this research.

This research provides an output signal for external devices, such as voltage high/low states or a PWM for servo motor controlling. The main application for this system is, when the spectrum of the EMG signal has been identified as a motion this action must be performed in a physical environment. To do the testing process of the EMG monitoring system, a prototype of an orthic skeleton of human hand is proposed. The design consists in mechanisms with three degrees of freedom, one for each output signal for the monitoring system. A possible device is shown in Figures 2, 3 and 4.

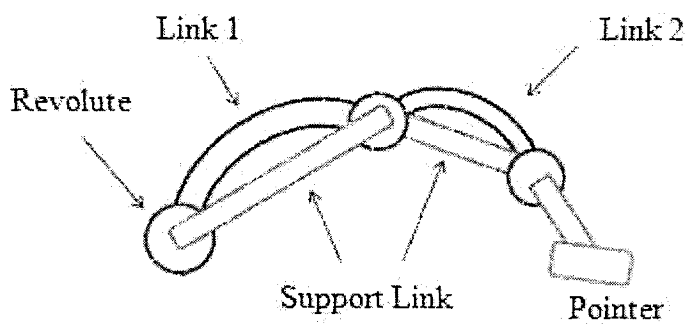

Figure 2. Frontal view of a device proposed to simulate a finger movement.

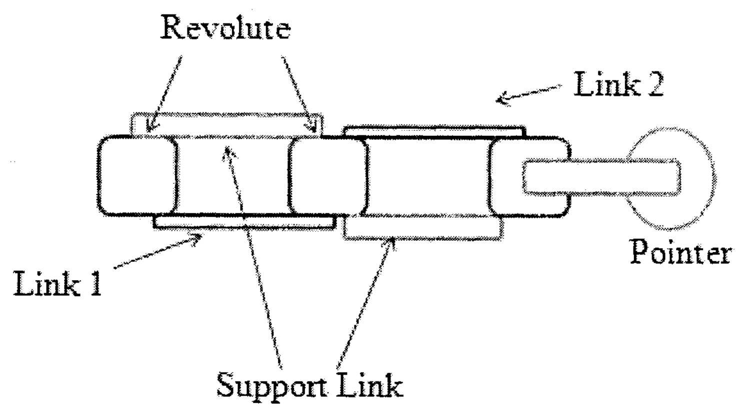

Figure 3. Lateral view of the device proposed to simulate a finger movement.

The main characteristic of the design is that the mechanism only needs an input motion in the first link while the rest are connected in a way that imitates the human finger motion. So each finger motion needs only one servomotor to perform the finger motion.

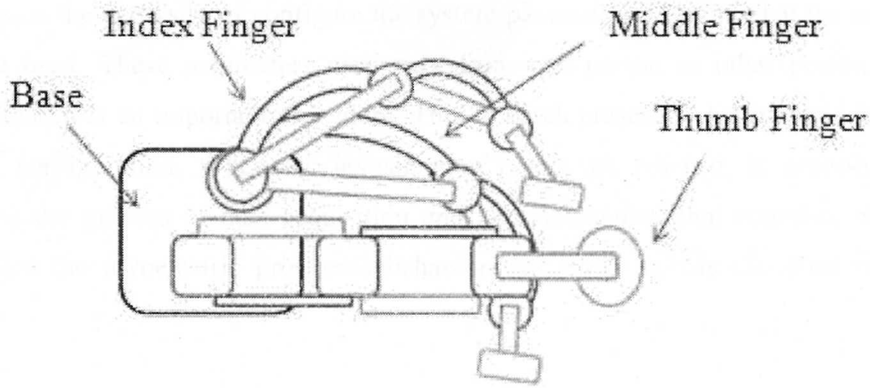

Figure 4. View of the device proposed for the three degrees of freedom.

The thesis purpose is to map the human arm in order to classify the EMG patters that produce motion in the index, middle and thumb fingers.

1.5. Study Scope and Limitations

The functions that carry out the existing prosthesis varies, it depend on the manufacturer and some cases on the characteristics that users specify, this can be a complex process that sometimes results in a user that could never familiarize with it, or in other cases, where the prosthesis is not considerate because they do not satisfy user requirements such as low mobility or expensive cost.

Develop an interface that is able to upgrade the EMG signals and that realize the communication with the system in order to provide an output signal for controlling. The acquisition uses a single channel to measure 4 states which are: (i) discriminating the noise or relax, (ii) index finger motion, (iii) middle finger motion and (iv) thumb finger motion, using spectrum magnitude analysis and a fuzzy logic classifier.

The system limitation which is commonly present in EMG monitoring systems, is the necessity of configure the system parameters any time that the system will be used. These parameters may vary from one person to other person then configuration is an important procedure. This research presents a list of steps for the system configuration When the investigation points are reached, is necessary to organize the process of data acquisition and experimentation that complete all the areas that the myoelectric prosthesis behavior and EMG signals classifier system involve.

1.6. Thesis Organization

The organization of this thesis includes chapter 1 that presents an introductory explanation of how the EMG signals are used in this research.

Chapter 2 presents the phenomena that originate the physiologic signals in the human body and characteristics that are important for this investigation, the EMG signals and alternative analysis procedures. An explanation of the EMG data acquisition procedure and the sensors used is presented. Finally a summary of Fourier Fast Transform analysis and Fuzzy Logic theory basics.

Chapter 3 describes the design of the electronic interface that will process the EMG signals and the best way of signals processing to do the correct interpretation of the physic stimulus that is generated. The procedure of acquisition signal, FFT and Fuzzy Logic algorithm design. The algorithm results are validated with MATLAB. The chapter concludes with the test and validation stage. Chapter 4 presents the instrumenation and testing system process. Finally, chapter 5 presents the conclusions and future work proposed for this thesis.

Chapter 2
State of the Art

This chapter describes the fundamental concepts of each area related with the design of EMG signals and its application in robotic prosthesis.

2.1 Background

The idea of analyzing and interpreting the human body behavior is, to tackle the physical and chemical internal properties that have been the centre point of investigations in several fields such as medicine and robotics. The definition and evolution of myoelectric signals is reviewed, since their origins until the existing applications based on the time line that Roberto Merletti proposed in his studies of prosthesis using electromyography signals [1].

A myoelectric signal is generated by a biochemical process of the human body and is converted to an electric signal [10]. The first investigator to discover it was H. Piper in Germany in 1912. In 1924 Gasser and Erlanger made similar investigations using an oscilloscope. Then Proebster watched signals generated from innervate muscles, starting officially the clinical EMG signal studies [10].

Electrodes were developed for obtaining EMG signals. Electrodes are the sensors that transmit the human body signals, which can be internal or superficial and transduce EMG signals to electric signals that an electronic device is able to process.

In 1929 Adrian and Bronk developed the concentric electrode, which is the most commercially used [14]. After Kueglber, Petersen, Buchthal, Guld, Gydikov, Kosarov, Pinelli, Rosenfalck and Stalberg defined as the fathers of EMG technology, introducing the first quantitative analysis of the Motor Unit Action Potential (MUAP), the MUAP is the depolarization and repolarization cell processes that occurs for a stimulation of a membrane in response to chemical body changes. Furthermore Uchizono, described the signal propagation in muscles and Willison, introduced the width signal analysis of EMGs in 1964 [11].

Technological and computational advances in the 70's and 80's made possible EMG signal analysis, however the MUAP process has a high computing cost. Nowadays this work requires only a few minutes. Some of the pioneers in this field were LeFever and De Luca which introduced the mathematical analysis for physiological signals and EMG signals. He was the first who discovered the information contained in EMG signals, and others as Guiheneud and McGill continued De Luca research [15].

Meanwhile Dimitrova and Lindstrom made remarkable contributions for the biophysical EMG signal understanding. One of the applications developed was the Myoelectric Control of prostheses. Although this control had been used before in the 40's, its real development was achieved between the 60's and 80's [1].

The superficial EMG signals are fundamental for the prosthesis control. It has been used for disabling, specifically in the arm and hand. During the 60's many significant advances were done in the prosthesis control field by countries as the URSS, Sweden, England, Japan, Canada and the USA.

The first commercial system of arm prosthesis was exported from the URSS to Europe and North America in 1960. Meanwhile investigations in Japan developed a myoelectric multifunctional hand. In Sweden, a recognition system based in a myoelectric control was developed. Furthermore in Canada in 1960, Scott and Dorcas developed the myoelectric tri-state control, which consists in the control of one device with three functions for a single muscle [1, 10].

The first myoelectric controllers worked with on/off mode for the electrical control of an energized arm, performing the open/close functions, this required one myoelectric channel for each open/close operation [1].

The energized prosthesis with myoelectric control caused a significant impact on clinical applications in the 1970's when they were used in people with arm or hand amputation, allowing a clinical evaluation of the functional advantages that these devices bring to end users.

Nowadays there is a vast research in electromyography processing systems as Simulations of EMG prosthesis such as Alonso A. et al. [20] which simulates the arm and hand motions in a virtual environment, in 2002. The system to model bio signals in from Rocon et al [19] which identify arm and forearm motions, in 2006. They use a configuration of single muscle for single motion.

There are researches that use artificial intelligent algorithms as Sandoval and Varila [21], which uses Neural Networks for the open and close hand motion in 2007. Another EMG signals processing algorithms such as Wavelets were used by Gila et al. [22] in 2009, which characterize EMG patterns with this methodology.

Energized prostheses with myoelectric controls show some advantages such as: (i) they are used without strings or harnesses that most of mechanical prosthesis need, (ii) the myoelectrical signal is not invasive and detected on the skin surface, (iii) the electric battery is possibly the most recommended power source that is able to be installed in a prosthesis, (iv) the controller can be adapted to a proportional control easily, (v) the electronic circuits are improved and minimized constantly, and the muscle activity required to provide the signal control is relatively small and similar to the required strain by an intact limb.

Some research about EMG using prosthesis are Harold et al. [23], using EMG hand signals to control a virtual prosthesis, while DiCicco et al. [24] used the EMG signals to control an orthic exoskeleton in 2007.

At this point, it is possible to understand that the electromyography studies present advances in fields such as computing, electronic and sensor technologies. Next section presents the main characteristics and the phenomena that produce EMG signals.

2.2 Anatomy of Physiological Signals

Three types of muscles compose human body: (i) skeletal, (ii) smooth and (iii) cardiac. Skeletal muscle moves the bones of the skeleton system. Each one is made by tiny fibers grouped together into bundles running lengthwise along the muscle called myofibrils, as is shown in Figure 5 [12]. Skeletal muscle is also called striated muscle or voluntary muscle. A conscious decision can shorten this muscle. The other types of muscle are controlled involuntary.

The smooth muscles are found in the internal organs like the digestive system, the blood vessels and the glands. Unlike skeletal muscle, these are not connected to bones. Instead, smooth muscle form tubes, pouches or sheets, which contract to move their contents, food is pushed from the mouth down into the stomach by smooth muscle in the esophagus.

The third type of muscles is the cardiac muscle or myocardium. This forms the wall of the heart. It contracts about once every second when the body is active and its motion pumps blood out of the heart and around the body. Many other muscles work only for a limited time and then become tired or fatigued. Cardiac muscles never rest, if they did the heart would stop and life would cease. Muscles work only by shortening (contracting) hence they can only pull their mechanical loads. Many muscles are arranged in pairs, where one pulls in one direction and the other pulls the opposite direction. Note that when one muscle contracts itself the other will relax and get extended.

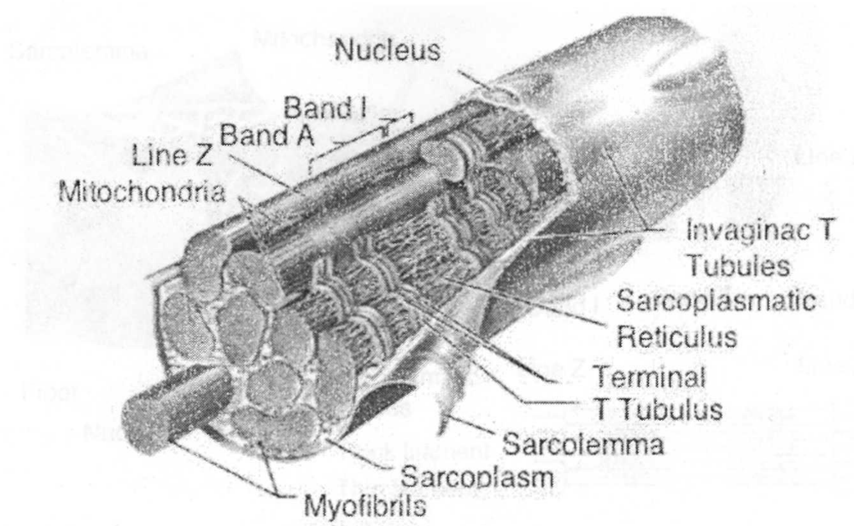

Figure 5. Internal muscle structure [12].

Muscles are controlled by tiny electrical messages sent along nerves (Figure 5) from the brain. The message tells the muscles when to contract, by how much and for how long. The nerves join a muscle at a special junction, which lie on top of the muscle fibers. When a message arrives from the brain at a motor end plate, it triggers a chemical messenger called acetylcholine. This sets off chemical and electrical reactions in the muscle, starting the process of contraction.

Muscle fibers are made up of bundles of myofibrils, which are protein filaments. There are two types of protein filament, the thicker ones called myosin and thinner ones called actin. When the chemical and electrical changes begin in the muscle, the actin filaments slide between the thick myosin filaments and the muscle becomes shorten. The filament grip on to each other partly as a result of the chemical reaction, which takes place, and partly due to teeth along their surfaces. Figure 6 shows the fibers and structure that compose the muscle internally.

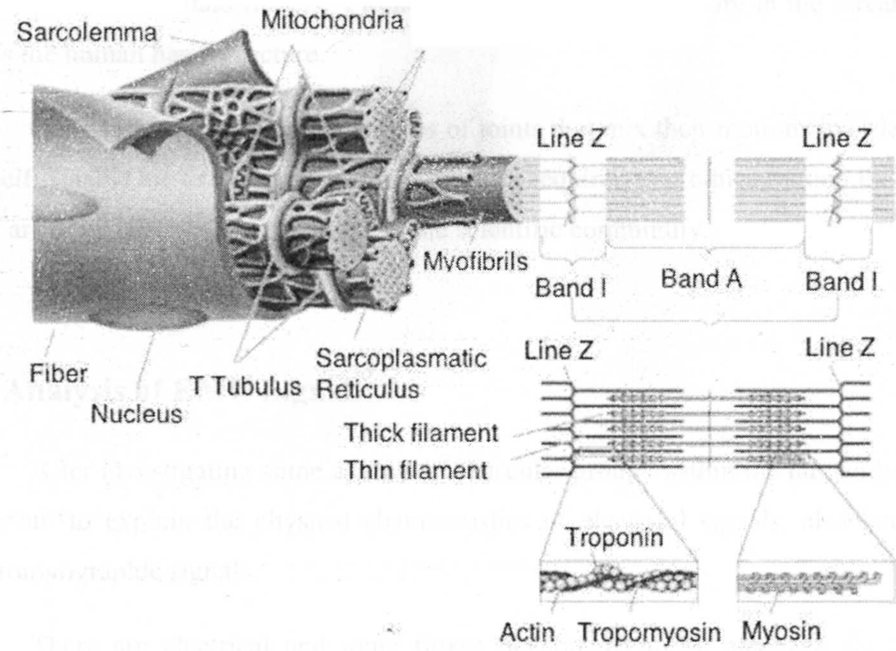

Figure 6. Fibers and myofibers in the muscle [12].

In fact each muscle fiber is contracted or relaxed. While more fibers receive the contract message, the muscle becomes shorter and the opposite muscle pulls. When the message of shortening cease, the chemical reaction between actin and myosin stops and the filaments are free, in other words the muscle is relaxed [2].

This research focus mainly on the muscles of the hand, forearm and hand. These muscles are on the top of the body and can be divided as shoulder and arm. The most important arm muscles are: biceps in the front side and the triceps in the backside, these are antagonist muscles, which means that their actions are contrary, either contraction or relaxation. The forearm has supination and pronation motions, which allows the turning forearm motion, the rotation of the hand and the fingers contraction and relaxation.

Human arm can slide softly or hit strongly as a karate punch, take a nail, write with a pen or press a keyboard, play a musical instrument and perform other kind of activities that require a wide range of motions and forces. Several muscles control the motion of the hands and fingers. Twenty pairs of these muscles are in the forearm that builds the human hand structure.

Our hand has many different types of joints that mix their motions in order to do a specific task. Due to the large group of muscles required to produce motion the design of an artificial task poses a challenge to the scientific community.

2.3. Analysis of EMG Signals

After investigating some aspects of muscular groups within the human body, its important to explain the physical characteristics of electrical signals, also known as electromyographic signals.

There are electrical and ionic fluxes phenomena to be analyzed for skeletal muscle. The potential action lasts 2 to 4 ms, is conducted along the muscle fiber at an approximate speed of 5 m/s. The absolute refractory period is 1 to 3 ms and post polarizations, with their related changes in the threshold to electrical stimulation, are relatively long [4].

Although the electrical properties of individual fibers in a muscle do not differ enough to produce a compound potential action, there are slight differences in the thresholds of the different fibers. In addition to any experimental stimulation some fibers are more distant from the electrodes receptors than other. Therefore, the size of the potential action recorded in a preparation with the entire muscle is proportional to the intensity of the stimulating current between threshold and maximum intensities.

It is important to distinguish between electrical and mechanical phenomena that occur in the muscle. Although normally a response does not happen without the other phases and physiological characteristics are different. Membrane depolarization of muscle fibers begins at the motor end plate, which is a specialized structure in the motor nerve terminal; the action potential spreads along the muscle fiber and initiates the contractile response. There is also a phenomenon called muscular twitch where an action potential causes a brief contraction followed by relaxation.

Electromyography is the process of recording the muscles activity in an oscilloscope. In humans, this can be done without anesthesia, with small metal discs that are placed on the skin over the muscle, which function like hypodermic needle electrodes. The record obtained from these electrodes is also called electromyography, or EMG. With needle electrodes is possible to capture the activity of individual muscle fibers.

Electromyography has shown that there is little or no spontaneous activity in skeletal muscles of normal individuals at rest. With minimal voluntary activity a few motor units produce discharge, and with increasing voluntary effort include increasing the activity units. Sometimes this process is called motor unit recruitment. Therefore, the degree of the muscle response depends in part on the number of motor units activated.

The firing rate in individual nerves, it is known that the tension developed during a contraction is greater than the obtained for individual shocks. Where the length of the muscle is an important factor to consider. Finally, the motor units fire asynchronously, resulting in individual muscle fiber response that merges into a smooth muscle contraction.

The most common diseases that are associated with the muscles and is the cause of amputations is called muscular dystrophy, which results in progressive weakness of skeletal muscles. Different types of dystrophies have been identified ranging from moderate to severe, in which the solution of a delayed amputation can be fatal. This disease has multiple causes, regularly attributed to mutations in genes of muscle proteins.

Mutations of genes of various components of the distrofanina-glycoprotein complex are the most important cause. The dystrophin gene is one of the largest in the body, and mutations can occur in many parts of it.

Some common diseases are: Deuchenne muscular dystrophy, where a severe form of the protein dystrophy called dystrophin is absent in the muscle. A less critical case is the Becker muscular dystrophy where dystrophin is present but with some abnormalities [5].

2.4. Techniques of EMG Signal Input

Once the physical and chemical characteristics of the electromyographic signals have been reviewed, it is necessary to determine the most appropriate technique to use in this electronic transduction system.

From [25], the physiological signals can be named in different ways, it depends on their application. Some applications of these signals and its approximate values of voltage and frequency are: (i) EOG samples the ocular activity, has a voltage of 0.01 mV and range from 0.1 to 10 Hz, (ii) EEG samples the brain activity, has a voltage of 0.1 mV and frequencies from 0.1 to 100 Hz, (iii) ECG samples the cardiac activity and has a voltage of 1 mV and range from 0.1 to 500 Hz, (iv) EMG samples muscles activity, has a voltage of 1 mV and frequencies from 20 to 500 Hz.

Then for EMG, muscle is the source of signals for myoelectric controllers where the user has suffered the amputation. Figure 7 shows a schematic diagram of the communication channel of EMG signals in the body, note that the signal originates at the cerebral cortex and passes through the spine to the corresponding muscle.

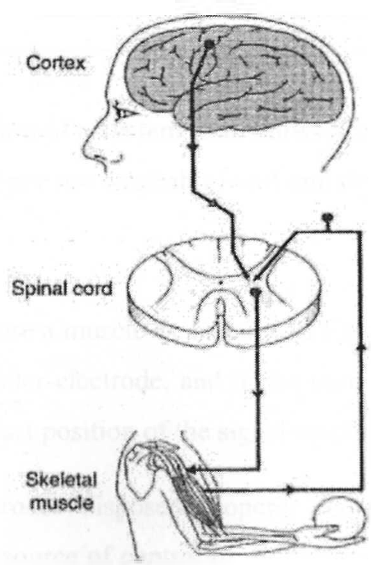

Figure 7. Diagram of the flow of information from EMG signals [1].

It is necessary to determine if the muscle surface is wide enough, to carry a pair of electrodes, in order to acquire the myoelectric signals from this muscle and be transmitted to a control channel. Figure 8 shows a diagram proposed by Parker and N. Scott [6] where is possible to see the difference between the system of a person with no deficiency or amputation and a person that requires prosthesis, more specifically, the Joint and Output area corresponds to the muscle which has a deficiency in an amputee or prosthetic needs.

A bipolar intramuscular electrode allows the isolation on a segment in the muscle and using the potential of motor unit action as a source control signal. Clinically it is not practical to use a transcutaneous invasive method, hence surface electrodes are more commonly used, which have some limitations, compared with the invasive type.

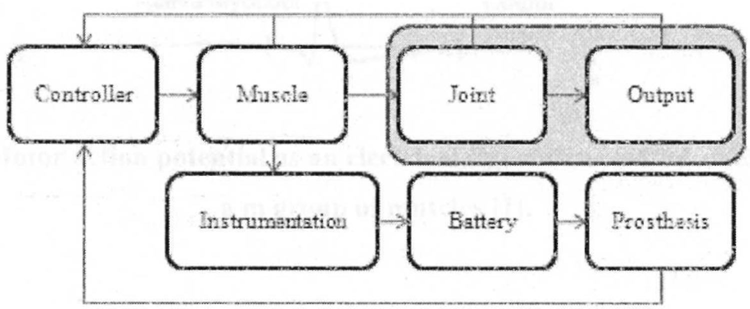

Figure 8. Block diagram of a system that shows a person without disability (their Joint and output are not available) and one that requires prosthesis [6].

The problem to use a muscle as a source of EMG signal is that sufficient surface area is required by an inter-electrode, and in the case of congenital amputees, there is uncertainty about the exact position of the signal reaching that muscle.

A pair of electrodes disposed properly acquires a signal from a group of muscles. This will be a source of control of multi-muscle signals and interpreted as the sum of the signals in time and space of the electrical activity of a group.

Furthermore a channel of myoelectric signals must include the group of muscles to sense the electrode and the volume of the driver needed between each muscle group and the electrode. Figure 9 shows that electrodes are arranged in a group of muscles and it can acquire the EMG signal corresponding to the signal sent from brain to the muscle group in order to perform a specific task.

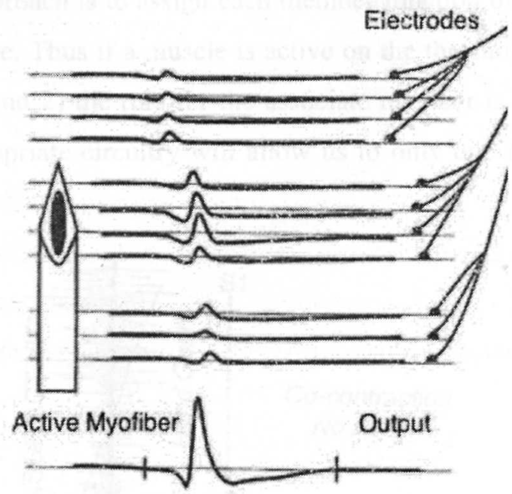

Figure 9. Motor action potential as an electrical signal detected by an electrode on a m group of muscles [1].

After determining the method for obtaining the inputs to the controller, either a channel or multichannel, the next step is to collect and organize information for processing.

2.5. Myoelectric Classifier Methodology

2.5.1.. Conventional Myoelectric Classifier

To start the process of enabling the EMG signals as input to the controller, certain features that are related to the signal and the planned motion by the user need to be extracted. Most commercial systems use an estimate of the variance of the signal as an input to the controller.

Most commercial EMG systems are based on the extent or level of encoding of the processed EMG active muscle either from a user. The encoding of the amplitude can be done in several ways.

A common approach is to assign each member function of the prosthesis from a separate control muscle. Thus if a muscle is active on the threshold line (S1 for muscle and S2 for muscle 1 and 2) the role for the associate member is selected, as shown in Figure 10. With appropriate circuitry will allow us to only one function is active at a time.

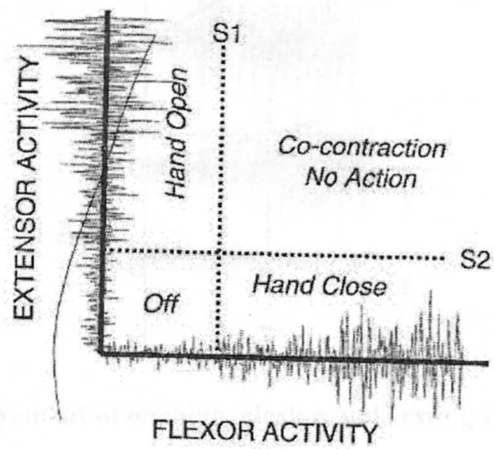

Figure 10. Coded amplitude classification of a signal using 2-channel EMG [1].

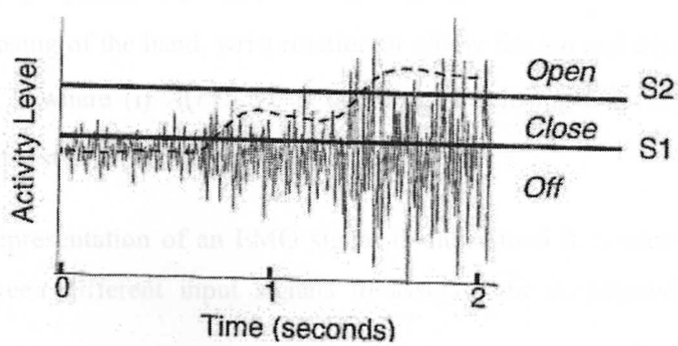

Figure 11. Coded amplitude classification of a signal using 1-channel EMG [1].

This approach enables to classify the selection of the muscle based on physiological functions but has the disadvantage of requiring two control muscles for each degree of freedom of the prosthesis. This limitation results impractical for higher-level amputees.

In theory, the full range of myoelectric signals produced from the relaxed state to the full contraction can be divided into several stages as shown in Figure 11, where each is associated with a threshold and a function for the device. The function is activated for this stage will then be activated if it exceeds the required threshold.

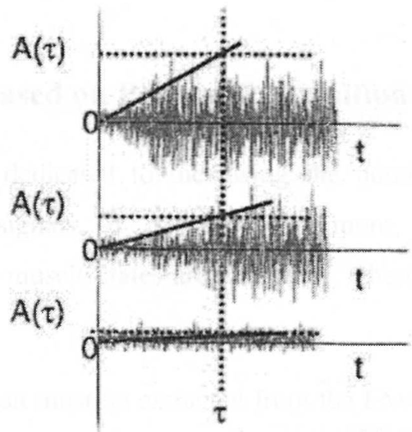

Figure 12. Measurement of opening, closing and resting EMG for hand [1].

In practice, the number of functions that an individual can control with good performance using this approach is limited to two per muscle control. Typically these are opening and closing of the hand, wrist rotation or elbow flexion and extension, as is shown in Figure 12, where (i) $A(\tau) > S2$ is opening, (ii) closing $S2 > A(\tau) > S1$ and (iii) the muscle is at rest at $A(\tau) > S1$.

Once the representation of an EMG signal is understood it is necessary to the identification between different input signals to assign their corresponding control function.

2.5.2. EMG Classification Strategy

With advances in computing devices and signal processing techniques have opened new possibilities for improved myoelectric controllers. The goals of current research in EMG signals classifiers are two, provide a better performance and present a more natural meaning of the effect of muscles motion. Both contribute to improving the skill and use of prostheses.

2.5.3. Classification Based on Pattern Recognition

If one method is dedicated to increasing the number of devices under the classification of EMG signals, it is clear that more sophisticated means for discrimination of different muscle states are necessary, where two stages are needed to achieve this:

1. More information must be extracted from the EMG signal about the state of the active muscle.

    a. Using multiple channels of EMG can provide the location of the number of muscle sites.
    b. Develop a set of tools that extract the most information from EMG signals and this will serve to discriminate different types of motions.

2. A system that is able to interpret information from the input signal and decide which kind of information has caused it.

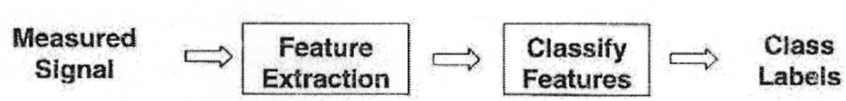

Figure 13. Problem of pattern recognition [1].

This suggests a pattern recognition approach based on EMG signal, as shown in Figure 13 wherein the signal flow starts in step 1 corresponding to the measurement of the signal, after the extraction of characteristics, and then it is necessary to classify the signal and programmed a respective action.

2.5.4. EMG Measurement Strategy

When obtaining myoelectric signals using surface electrodes, the primary concerns regarding the placement of the electrodes that collect the signal is to capture as much information of muscle activity as possible. To accomplish this, when the electrodes are placed in the upper arm has two possibilities are set:

1. A single bipolar channel with bipolar electrodes placed at a large distance between each other.

2. Multiple bipolar channels, with the pairs of electrodes placed close to each other.

Figure 14 shows the typical patterns corresponding to flexion and elbow extension, pronation and supination of the forearm by a single bipolar channel, according to the patterns of EMG activity was recorded using a pair of simple bipolar electrodes, placed on the biceps and triceps of a patient.

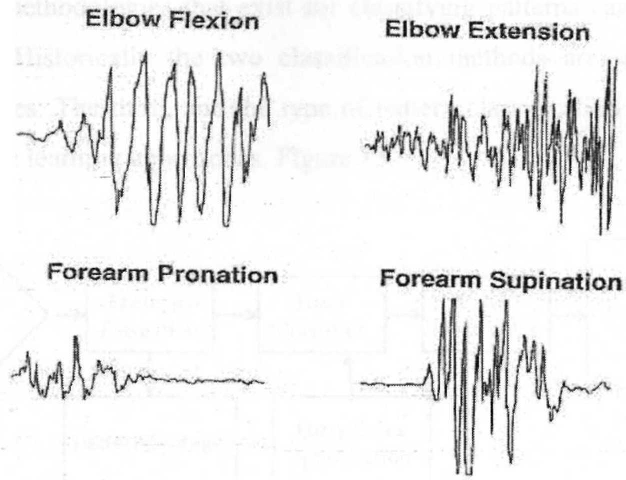

Figure 14. Some patterns on EMG activity [1].

This pattern is exhibited as temporal waveforms. With a group of patterns derived from the same contraction, the structure that characterizes the pattern is consistent enough to maintain a visual distinction on the different types of contractions. The above mentioned classifications have been developed by Hudgins [8] and use these definitions to understand stage characteristics that facilitate the systematic classification.

2.5.5. Features Extraction and Pattern Classification

The most used features that describe the EMG signals were the prolonged activity index, the absolute value or some similar measure. Motivated to provide more information on each channel EMG [1], multivariate characteristics have been proposed and used successfully. Initially, limited by the computational capacity of power sources, these characteristics were based on statistics in the time domain, such as: (i) variance, (ii) fourier analysis, (iii) wavelets, (iv) correlation, etc.

The current approaches seek to exploit the temporal structure of the EMG patterns using Fourier transforms and spectrum analysis on larger orders.

Practical methodologies that exist for classifying patterns can be grouped into three categories. Historically the two classification methods are: (i) statistical and synaptic approaches. The third, and the type of pattern classification with more recent development is the learning approaches, Figure 15.

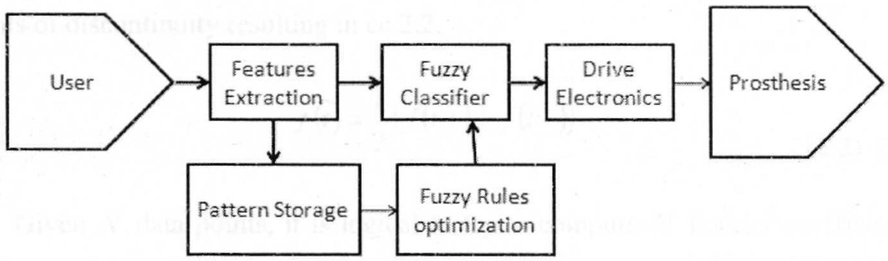

Figure 15. Scheme based on the EMG for a fuzzy classifier.

The system starts with a drive that extracts the information from the user's arm through the electrodes, then these signals are be coded using fuzzy logic classifier, the system compares the input signal with a stored signal as stated previously, the results of this comparison are interpreted by the system as a given motion.

By using a communication interface, the program will receive this signal converted to a digital signal, and according to their algorithm, the prosthesis can react to the motion that has been invoked.

2.6. Fast Fourier Transform

A common used method to analyze the EMG signals is the Fourier series and the Fourier Transforms, while based on the spectrum analysis an EMG motion it is possible to represent a pattern that describes itself [16].

Assuming that this signal f is periodic with a period a, and N values are regularly spaced over one period, the equation for f is (ec 2.1).

$$f\left(k\frac{a}{N}\right)=y_k,\quad k=0,\ldots,N-1 \tag{2.1}$$

The signal $f(t)$ is thus assumed to have been sampled at regularly spaced times separated by a/N units. If the Fourier series of f converges point wise to f and that at points of discontinuity resulting in ec 2.2.

$$f(t)=\frac{1}{2}(f(t+)+f(t-)) \tag{2.2}$$

Given N data points, it is logical to try to compute N Fourier coefficients C_n. Since the coefficients tend to zero as n tends to infinite it is possible to compute C_n for n = - N/2, … N/2-1 in the ec 2.3.

$$C_n=\frac{1}{a}\int_{-N/2}^{N/2-1} f(t)e^{-2i\pi n\frac{t}{a}}dt \tag{2.3}$$

The discrete Fourier transform applies to complex-valued vectors, hence to the case where y_k is real-valued. However in this case it is possible to reduce the cost of computation by half by treating two sets of real data with a simple complex transformation to compute the transforms of two real vectors x_k and y_k in the ec. 2.4.

$$\frac{(x_k)\rightarrow(X_n)}{(y_k)\rightarrow(Y_n)} \tag{2.4}$$

If $X_{N-1}=\overline{X}_n$ and $Y_{N-1}=\overline{Y}_n$, let $z_k=x_k+iy_k$ and denote the transform of z_k by Z_n (ec 2.5).

$$(z_k)\rightarrow(Z_n)\qquad Z_n=X_n+iY_n \tag{2.5}$$

But note that X_n and Y_n are not necessarily real with this notation (see ec 2.5).

$$X_n=\frac{1}{2}\left(Z_n+\overline{Z}_{N-n}\right)\qquad Y_n=\frac{1}{2i}\left(Z_n+\overline{Z}_{N-n}\right) \tag{2.5}$$

It is only necessary to compute these values for $n = 0,\ldots N/2$, since the values for n between $N/2$ and N-1 will have already appeared as their conjugates. Thus it is sufficient to compute the transform of z_k to obtain the transforms of x_k and y_k. It is also possible to compute the Fourier transform of a simple real vector with N components by using a transform of length $N/2$ (see Figure 16).

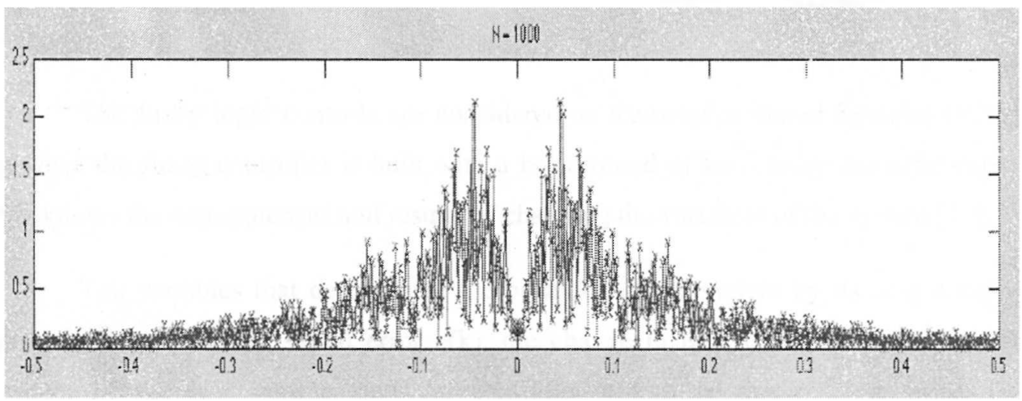

Figure 16. Typical response of an FFT analysis of an EMG.

2.7. Fuzzy Logic

There is an inherent impreciseness presenting our natural language when we describe phenomena that do not have sharply defined boundaries. Fuzzy sets are mathematical objects modeling this impreciseness. Fuzzy set theory provides mathematical tools for carrying out approximate reasoning processes when available information is uncertain, incomplete, imprecise or vague.

By using the concept of degrees of membership to give a mathematical definition of fuzzy sets, we increase the number of circumstances encountered in human reasoning that can be subjected to scientific investigation.

Humans do many things that can be classified as control. Examples include riding a bicycle or hitting a ball with a bat. We do not have the benefit of precise measurements, or a system of differential equations, to tell us how to control our motion, but humans can nevertheless become very skillful at carrying out complicated tasks.

The explanation of this is that humans learn through experience, common sense and coaching to follow an untold number of basic rules of the form "if..then". The use of basic rules of this form is the basic idea behind fuzzy control. Linguistic variables such as fast, slow, large, middle and small are translated into fuzzy sets; mathematical versions of "It..then.." rules are formed by combining fuzzy sets that defines the system behaviour [18].

The fuzzy logic controls are considered as Knowledge Based Systems (KBS), because the fuzzy controller is built with a background of knowledge from the expert that knows the consequences and results of changing the variables of the system [19].

The variables that determinate the behavior of the system by its output signal named y(k), the actual signal error e(k), the change in time of this error e'(k) with respect of the last sample, and the controller output or manipulation u(k). The discrimination procedure of these values it is possible to obtain the current state of the system and to predict the system behavior in order to take actions.

It is also possible to define this expert systems with a series of rules that represents the if..then conditions. The values that variables can take are defined in terms of:

- e = > NB, N, ZO, PS, PB.
- e'(k) = > NB, S, P B.
- u'(k) = > NB, NS, ZO, PS, PB, DC.

Where N means a negative value, P is a positive value and the terms B reefers to big, S is small, ZO means zero and DC is a drastic change in the current value of the measured variable. These groups of rules are classified in actives and restrictions. The actives are evaluated for each sample time, and restrictions are actives just when a precedent rule has been satisfied.

As EMG signals patterns can be fuzzy for some sample times and the use of a classifier based in fuzzy logic can provide us the best system response possible than a crisp classsifier which is based on common heuristic.

Chapter 3
Design of the EMG Monitoring System

The method for the construction of the monitoring system consists of 4 stages. The method to desing the EMG monitoring system is shown in Figure 17.

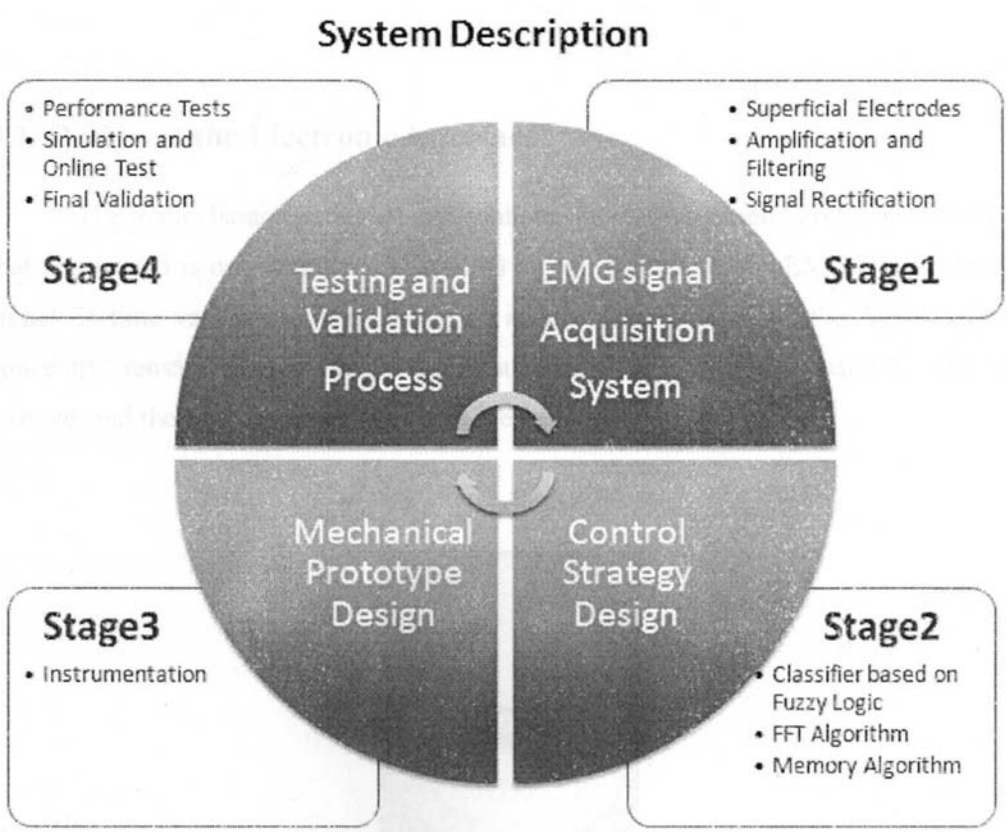

Figure 17. Stages involved in the system design process.

The stage 1 concerns the study of electromyography signals and their acquisition using surface electrodes.

After knowing the EMG signal characteristics follows the process of developing the electronic circuit that will be able to interpret the electrical impulses to discriminate between patterns using an amplification, filtering and rectifying processes. Then it would be easier to differentiate between what type of signal is being received, either opening or closing of the hand or finger motions.

Subsequently, the stage 2 is the interface that is able to receive the EMG signals from the electronics and to classify the motion that the user signal sends through the electrodes. Then the stage 3 that consist in the implementation of the system using an instrumentation circuit based on LED's. Finally on stage 4, are the performance and the validation of the system.

3.1. Design of the Electronic Interface

The main characteristic that differentiates this investigation to other prosthesis is that the motion is originated from an EMG signal. By nature, the EMG is a stochastic signal, is time variant and non-linear. To acquire the EMG signal the Ag/Cl surface concentric reusable electrodes are used, superficial electrodes are easier to add and remove, and their cost is lower than invasive methods.

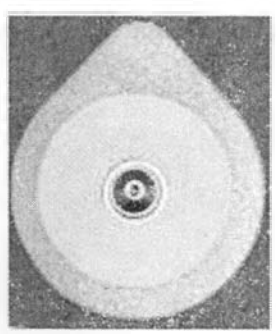

Figure 18. Ag/Cl surface electrode for EMG

During the experimentation many electrodes brands were used as 3M, BioProtech and MediTrace, each one has its advantages and disadvantages. The most suitable for this research are Meditrace electrodes, they are smaller and its adhesive performance was greater at removing and reuses. An example of the surface electrodes is shown in Figure 18.

The electrode is connected to the electronics using a wire that inserts itself in the top side of the electrode, this is an easy way of connecting and disconnecting but is also a noise source, noise is added to the input voltage signal when the wire moves and this modifies the pattern classification. There are a few configurations for EMG signal detection, for this investigation we will use an active electrode (-), a reference electrode (+) and a neutral electrode (ground). From the literature, the EMG surface technique recommends the use of the active electrodes and the references located less than a centimeter from each other over the sensing muscle. For 4 motions is commonly to use a single channel. The best electrodes location is found after experimentation procedures. In order to diminish the instrumentation noise caused by wires, and other connections a filtering process is used. Literature recommends using a first order high pass filter with frequency of 33 mHz because low frequency noises can produce a DF offset.

As the EMG input signal is in the order of mV, an amplification circuit is needed. The AD620CN Op amp is commonly used in biomedical instrumentation, it has a RG input that depending of the resistor that is located is the gain factor, amplify factor must be more than 100 to obtain a signal easy to process (approximately plus than 0.5 V) using a resistance of RG = 500 Ohms.

The circuit that describes the first order filter plus the amplifier with a gain of 100 is shown in Figure 19.

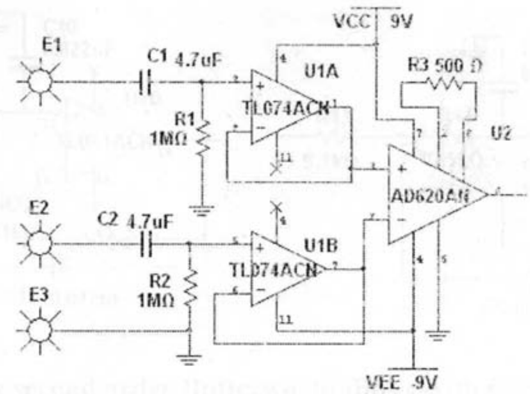

Figure 19. Electrode inputs followed by the high pass first order filter and the amplification using an AD620CN.

The parasite signals originated during instrumentation have bandwidth frequencies between 0 and 20 Hz, this system uses a TL074CN OpAmp as a second order Butterworth high pass filter is with a cut off frequency of 20 Hz, see Figure 20.

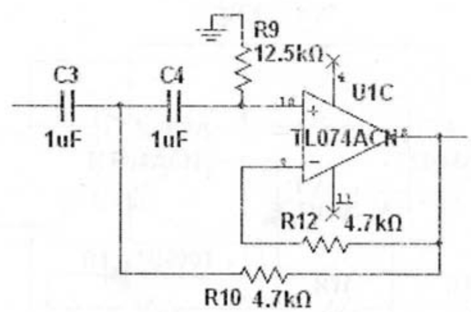

Figure 20. High pass second order filter with fc = 20 Hz.

As the literature mentions that the EMG bandwidth is from 20 Hz to 500 Hz the next step is to design a low pass second order Butterworth filter with a cut off frequency of 500Hz. Although its performance was good using a filter with fc = 500 Hz during experimentation, a low pass second order Butterworth filter with fc = 450 improved the circuit performance. Both circuits are shown in Figure 21.

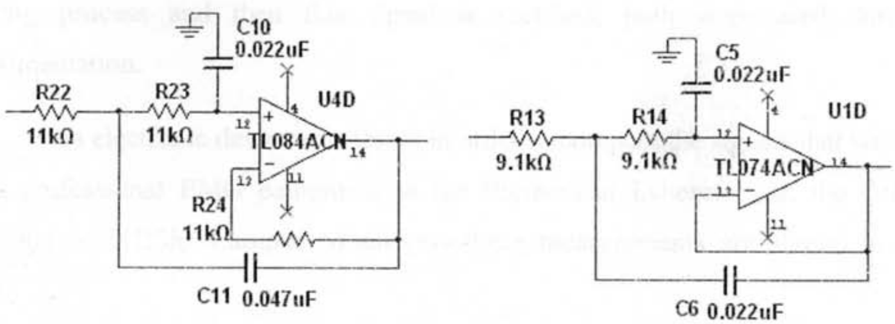

Figure 21. Low pass second order Butterworth filters with fc=500Hz and fc=450Hz respectively using TL047CN OpAmp.

The output signal is amplified and filtered, but an additional signal conditioning is needed. A rectifier block which output is the absolute value of the input signal is implemented using the circuit of Figure 22.

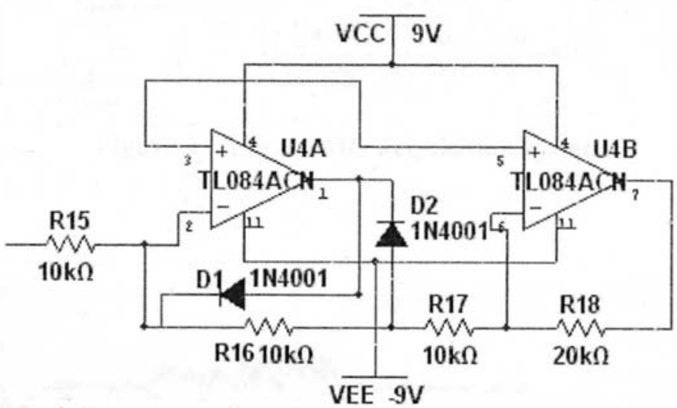

Figure 22. EMG signal rectifying.

Finally the design of the electronic interface for acquiring the EMG signal is ready. The Figure 23 shows the complete diagram of the system using MULTISIM Software and Figure 24 shows the output signals which are the original EMG after filtering process and then this signal is rectified; both were used during the experimentation.

This electronic device was tested in order to compare the signals that were given using professional EMG equipment in the Biomedical Laboratory in the School of Medicine of ITESM Campus Monterrey, these measurements are shown in section 3.1.2.

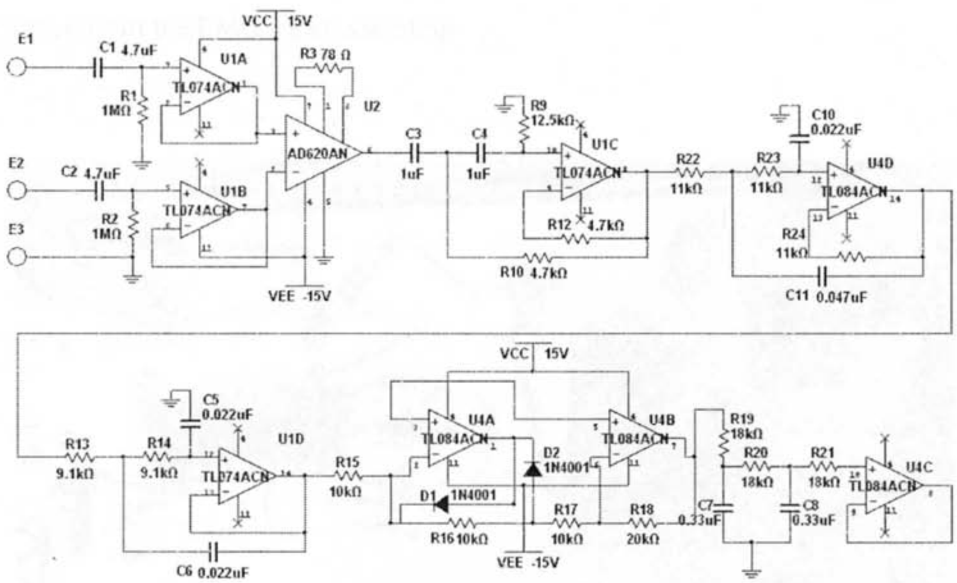

Figure 23. Final EMG acquisition system.

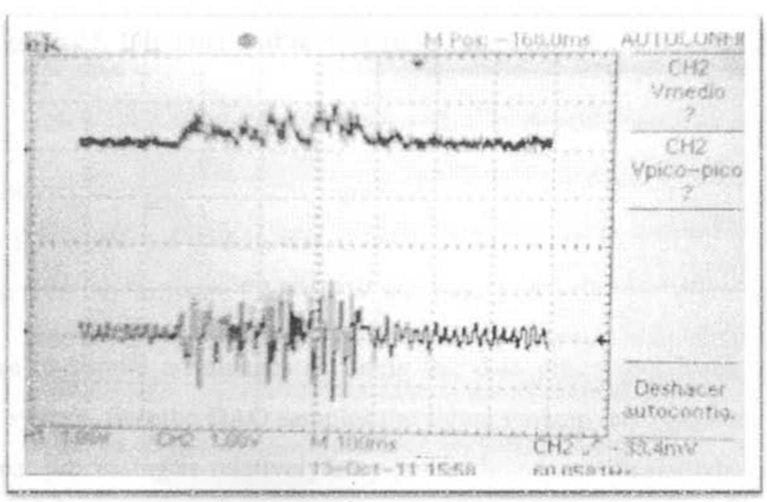

Figure 24. Output signals. 24 a) is the original signal and 24 b) is the rectified.

3.1.1. EMG Signal Acquisition Methodology

The previous section presented the design of the electronic interface where the EMG signal is sampled. This section explains the hardware behavior and some considerations to the sampling.

The electronic filtering and rectification design is shown in Figure 25, the system was built in a PCB but some modifications were done to get the best performance of the EMG signal sampling.

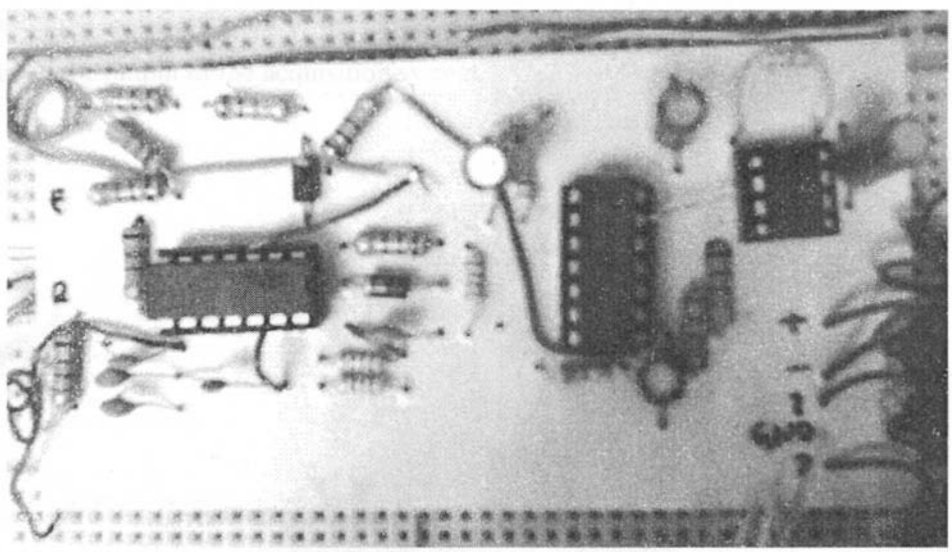

Figure 25. Filtering and rectification process of the EMG signal.

At the beginning, the system supposed to work with the original EMG signal sampled, at this point the system was considered to be sampled using a DAQ to the interface and then the Software LABVIEW will process the data and algorithms.

There are some advantages of doing the data processing using a DAQ and LABVIEW system, first the DAQ samples the signal without any hardware limitations, and the signal processing is relatively easy just adding some blocks where algorithms are already embedded, the disadvantage of using this system for the EMG signal processing is that the system is not a portable device, because there is no hardware to process the LABVIEW algorithms.

Another alternative to do the data processing is using Arduino chipsets, this brings the portable characteristic and the simple programming, but processing the complex algorithms that this thesis conceived as FFT not provide acceptable results and fast interaction.

The FEZ Panda II was chosen as the best alternative (Figure 26), given that EMG signal has sinusoidal wave form with positive and negative values, but the FEZ Panda II only measures positive analog input signals from 0 to 3.3V, this is the reason of adding a rectifier circuit in the electronic design, and then only positives values were given at the output of the acquisition system.

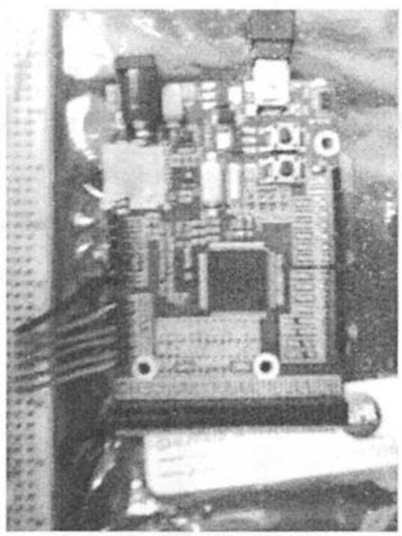

Figure 26. Fez Panda II integrated circuit.

The next step is to elaborate a standard finger motion for each degree of freedom and since there are many ways to perform finger motions, then is necessary to standardize the movements how each finger motion is performed.

The first position is the relaxation position (see Figure 27) when there is no finger motion and the system must classify it as noise.

Figure 27. No motion then noise is detected.

The second position is the middle finger motion (see Figure 28), if this motion is performed then the system identifies it and stops the relax position, then the algorithm set in the output signal which can be a led indicator or a PWM output to a servo motor which is located in the middle articulation.

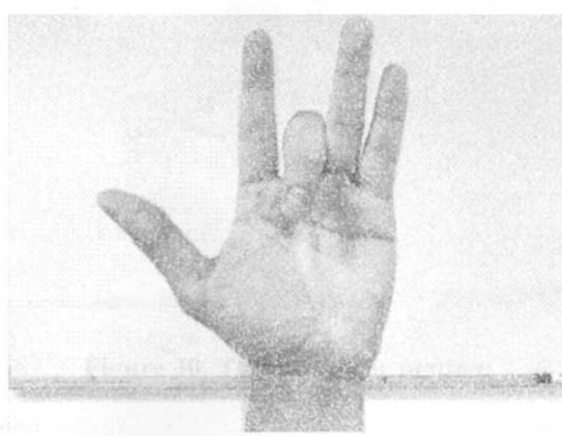

Figure 28. Middle finger motion.

The third position is the index finger motion (see Figure 29), if this motion is performed then the system identifies it and stops the relaxation position, then the algorithm set in the corresponding output signal. And finally the same process for the fourth position that consists on the thumb finger motion (see Figure 30).

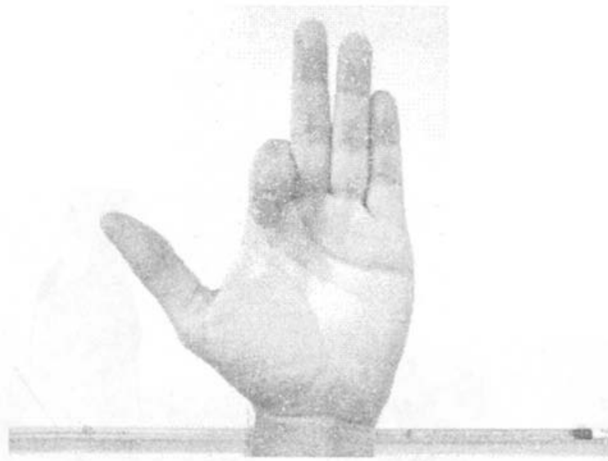

Figure 29. Index finger motion.

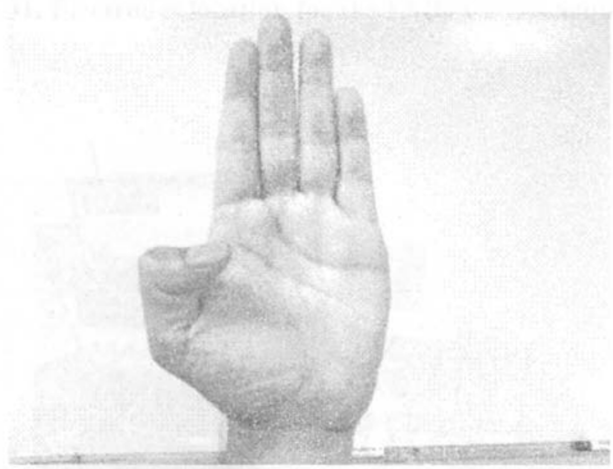

Figure 30. Thumb finger motion.

The last consideration is the location of the electrodes. many positions were tested from the literature.

The electrode location chosen for this thesis is shown in Figure 31, resulting in the best EMG signal performance for the three finger motions.

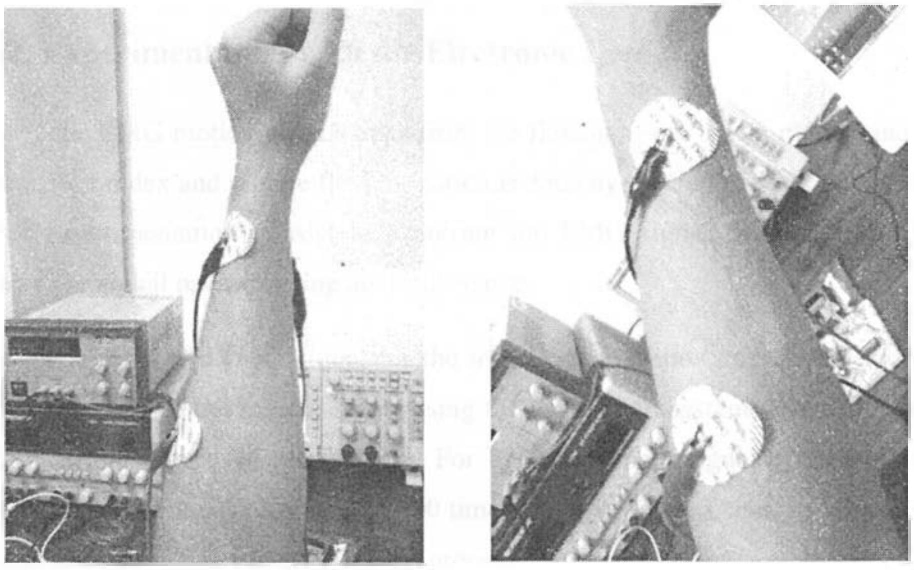

Figure 31. Electrodes location for the EMG signals acquisition.

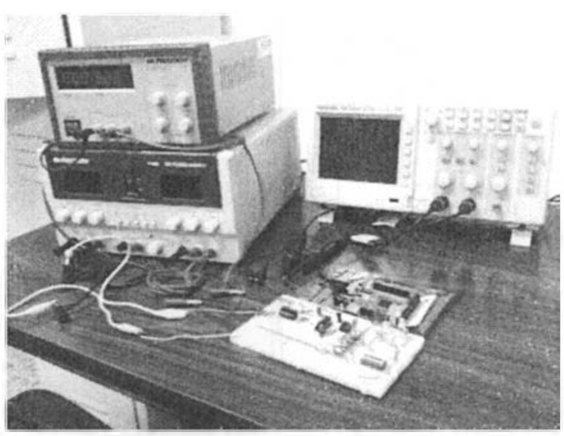

Figure 32. EMG Monitoring system hardware.

Finally the system input voltages were adjusted to work with 9 Volts, then only a single 9 Volt battery is needed to energize the electronic circuit, doing the system portable. For the experimentation process a two voltage source to obtain de +/- 9 Volts and an additional 3 Volts source for the LED and servo motors were used. The final system is shown in Figure 32.

3.1.2. Experimentation with the Electronic Design

The EMG motion signals arise from the flexion of the index, middle and thumb fingers. The index and middle flexion motion is done by the Superficial Fingers Muscle, so the experimentation consist in acquiring the EMG signal from this muscle and observe the signal patterns using an oscilloscope.

The registered input signal for the index finger motion and the flexion motion that corresponds to the middle finger using the acquisition system designed before are Figure 33 and Figure 34 respectively. For both. the upper signal corresponds to the EMG original input signal amplified 100 times and then filtered, and the lower signal is the output of the EMG signal rectifying process.

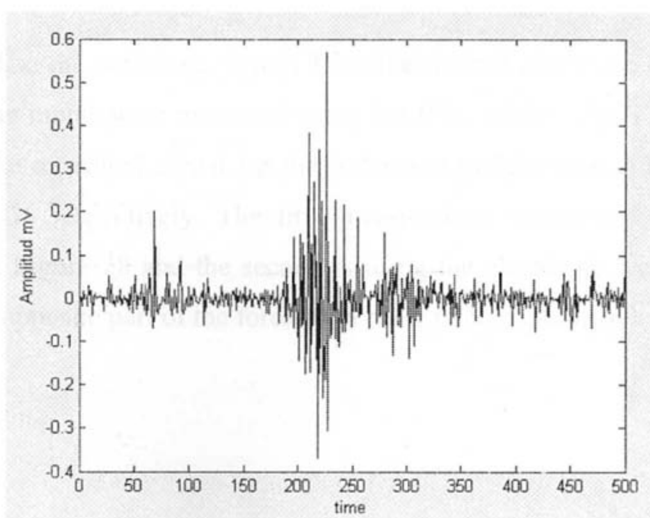

Figure 33. EMG signal of the Index finger motion.

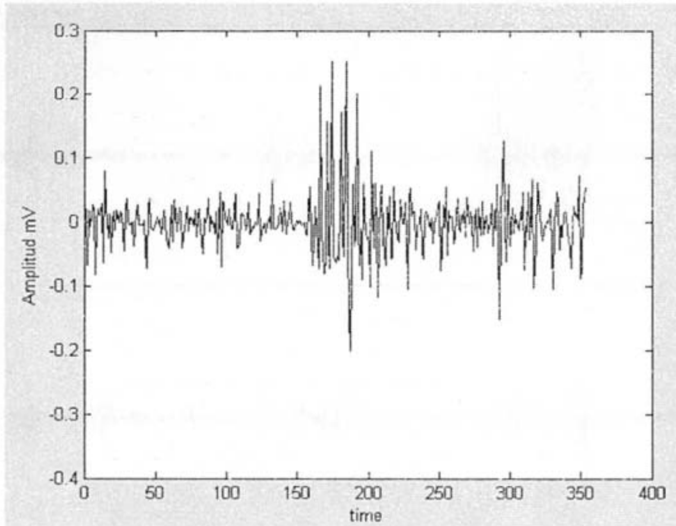

Figure 34. EMG signal of the Middle finger motion.

At this point a first observation of the signals can be done, where the behavior of the middle EMG has a diminishing amplitude level until it reaches a minimum then the signal increases and finally stabilizes, while motion for the index finger flexion is almost similar but with an inverted effect and has a larger amplitude; the signal increases until it reaches a maximum value and then decreases and stabilizes. This can be a first approach to distinguish both motions and its pattern.

To validate the measured signals from the desired electronic EMG acquisition system, the same inputs were measured using the BSL BASIC SYSTEM from Biopac System, Inc. The measured signal for the index and middle motion are shown in the Figure 35 and 36 respectively. The first measurement correspond to the electrode locations of the Figure 28 and the second is using the electrodes located in the same place but in the opposite part of the forearm in order to acquire the thumb finger motion.

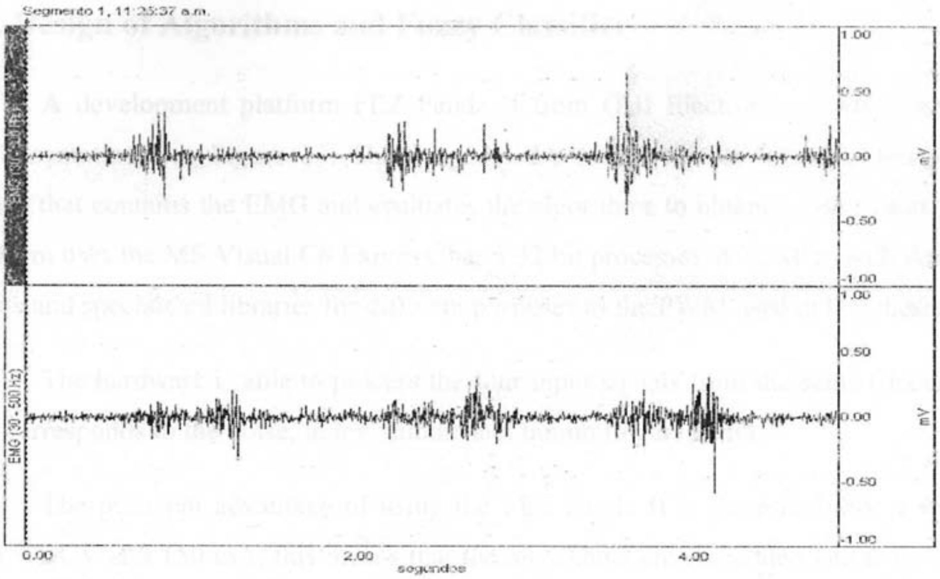

Figure 35. EMG signal of the Index finger motion with the EMG commercial kit.

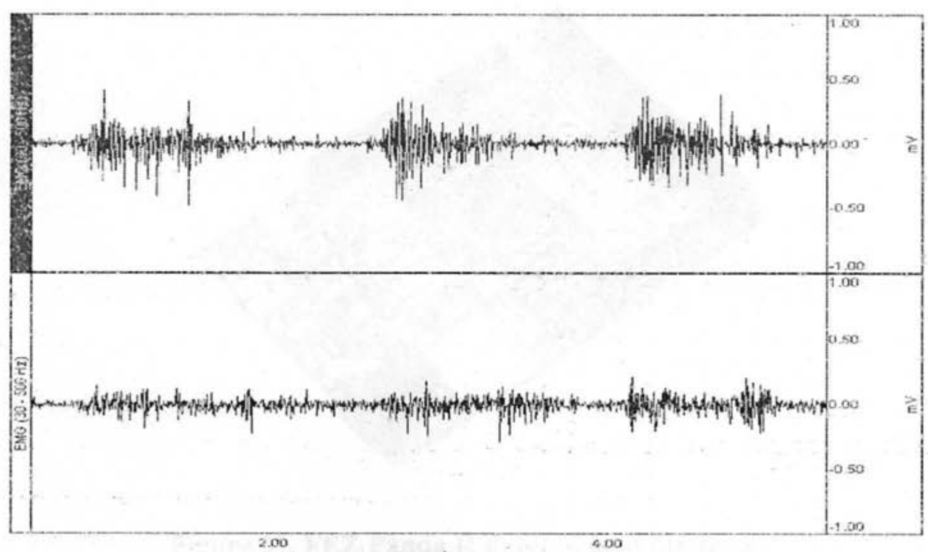

Figure 36. EMG signal of the middle finger motion with the EMG commercial kit.

After using a commercial kit to observe the EMG signal it is possible to determine that the behavior of the EMG acquisition system designed is acceptable.

3.2. Design of Algorithms and Fuzzy Classifier

A development platform FEZ Panda II from GHI Electronics is used for the implementation, see Figure 37. This acquires the output signals from the electronic device that contains the EMG and evaluates the algorithms to obtain a final result. The platform uses the MS Visual C# Express, has a 32 bit processor at 72 Mhz, with Analog inputs and specialized libraries for different purposes as the PWM used in this thesis.

The hardware is able to process the four input signals from the same Channel 1 that corresponds to the noise, index, middle and thumb fingers EMG.

The principal advantage of using the FEZ Panda II is the portability it works with 9 DCV and 150 mA, this means that the algorithms are embedded and there is no need to use a computer to assist the processing. A possible disadvantage is that programming in C# algorithms might pose a challenging task although code can be developed for new and complex modifications of the algorithm if necessary

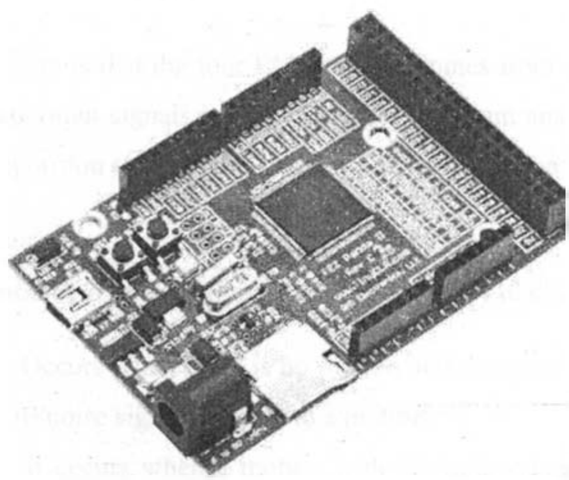

Figure 37. FEZ Panda II development platform.

The Algorithm of sampling reads the input signal and saves it in matrix length of 1024 samples, and then that matrix was evaluated using the next algorithm, meanwhile the input signal was saved in a second matrix in order to save the information during the processing. If the signal is detected as noise is deleted and then the last saved matrix now is analyzed and then the sampling procedure continues until a motion is detected.

3.2.1. Sampling and FFT Algorithms

The algorithms were developed using the C# language first, then the results were compared with MATLAB functions.

The 60 Hz frequency is present in the voltage sources and its aliasing, although these frequencies won't exist when the system voltage supply are DC batteries.

Once the signal is filtered the next step is to evaluate the spectrum with the Fast Fourier Transform (FFT) algorithm. The spectrum of the signal is the most important part for the identification process. Each muscle emits different frequencies in its EMG signal, as for instance, the measurement from the middle finger and the index finger motions has a different spectrum each one.

The problem here is that the four EMG signals comes from the same muscle, so the FFT of both EMG input signals results in similar spectrum analysis, that is why at the end of the FFT algorithm an additional sentence that obtains the FFT magnitude was implemented.

There are four possible resulting signals that are necessary to classify:

- Noise Signal: Occurs when there is no motion and the system must not start the processing until noise signal changes to a motion.
- Index Finger: It occurs when a motion with the index characteristics from the EMG signal is detected in the input.
- Middle Finger: It occurs when a motion with the middle characteristics from the EMG signal is detected in the input.
- Thumb Finger: Finally for thumb, is necessary that the system rejects the signals that may appear from the motion of index and middle fingers and to detect only the thumb finger characteristics on the EMG signal.

Using this electrode location it is possible to observe all the fingers (also ring and little finger), but to classify between each other a complex algorithm is needed.

The Figure 38 shows a noise signal, this is the original EMG input signal, note that there is no change in amplitude or considerable disturbances in the noise signal, and the second signal (see Figure 39) is the result of applying FFT algorithm.

The main characteristic in FFT that allow us to distinguish between noises and when there is a motion in the signal, as we can see in next pictures, is that there are noticeable changes in the magnitude of the FFT. In conclusion when the signal is a noise input signal, the system may continue sampling until there is a motion detected.

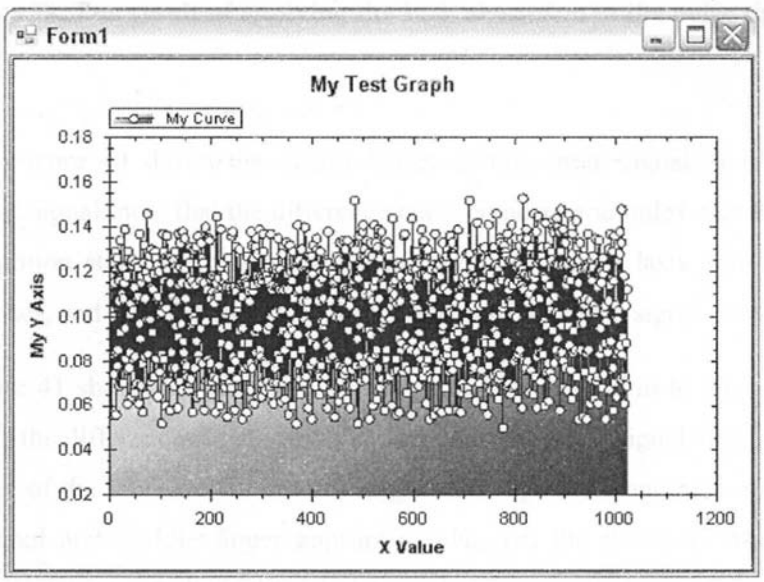

Figure 38. Noise EMG input signal.

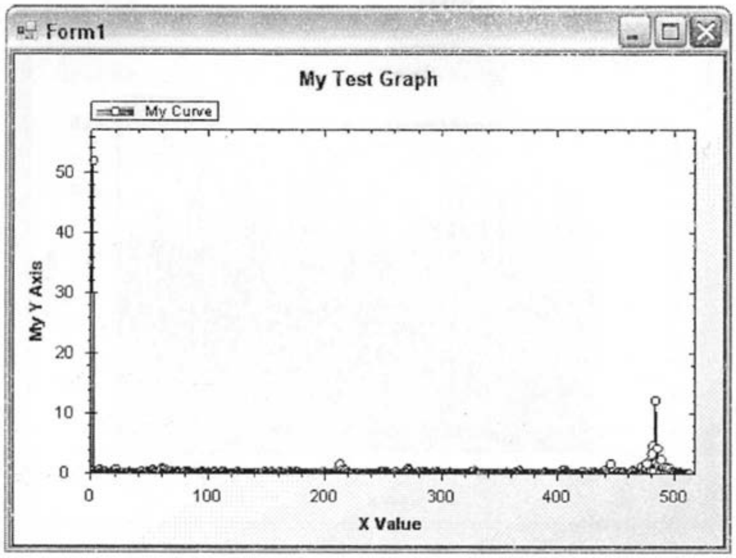

Figure 39. The result of applying the FFT algorithm to the noise signal.

The Figure 40 shows the middle finger motion input signal. It is shown the original input signal, note that the difference between noise and index signals is drastic, when the motion starts there is a change in amplitude and it lasts until the muscle motion finishes, and then the energy is diminished until the noise signal comes back.

Figure 41 shows the results of applying the FFT algorithm to the middle input EMG signal, the differences in the result compared to the noise signal are: (i) the values in magnitude of the FFT coefficients are bigger, although the magnitude of the Energy in noise signal and middle finger appears similar, (ii) the threshold *MaxOS* is not reached during relaxation, these characteristics allow classify the signals.

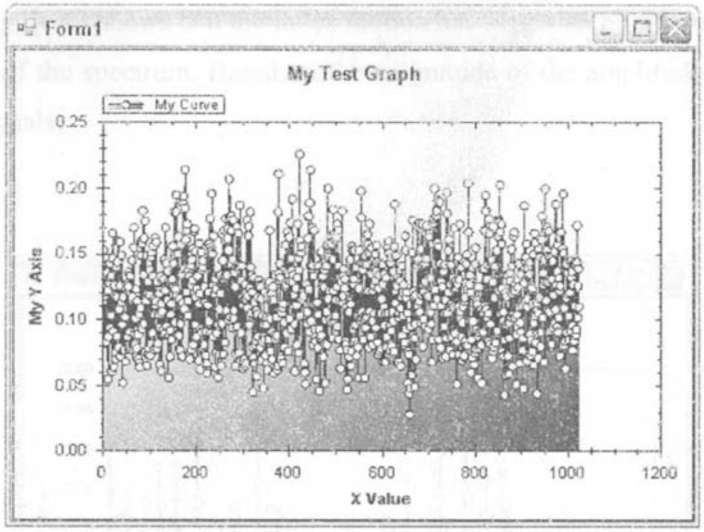

Figure 40. Middle EMG input signal.

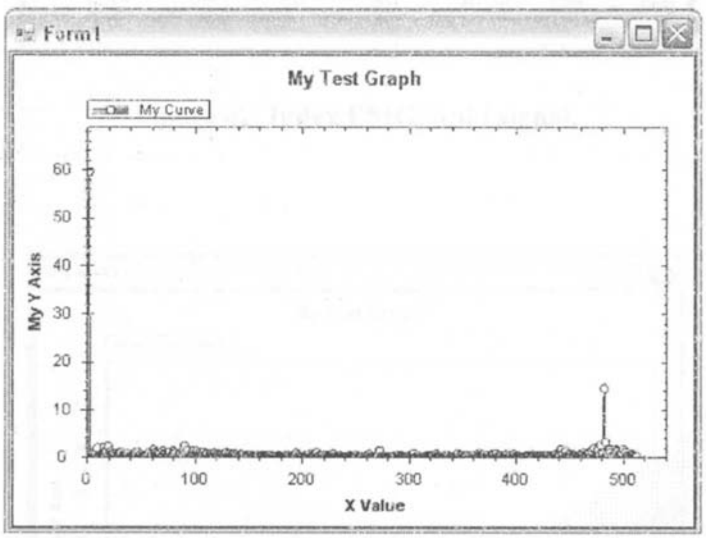

Figure 41. The result of applying the FFT algorithm to the middle motion.

Figure 42 shows the index finger motion input signal. The difference between the index and middle signal is that the energy that the muscle contribute for the index finger motion is bigger, so the EMG signal results in bigger changes in amplitude and the duration of the motion is also longer than middle motion.

The Figure 43 shows that the index motion has bigger amplitudes that contribute to the energy of the spectrum. Based on the magnitude of the amplitude is possible to classify the signals.

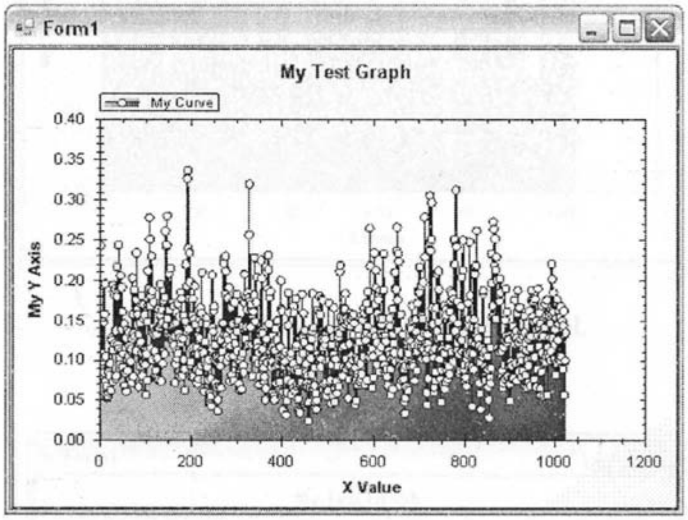

Figure 42. Index EMG input signal.

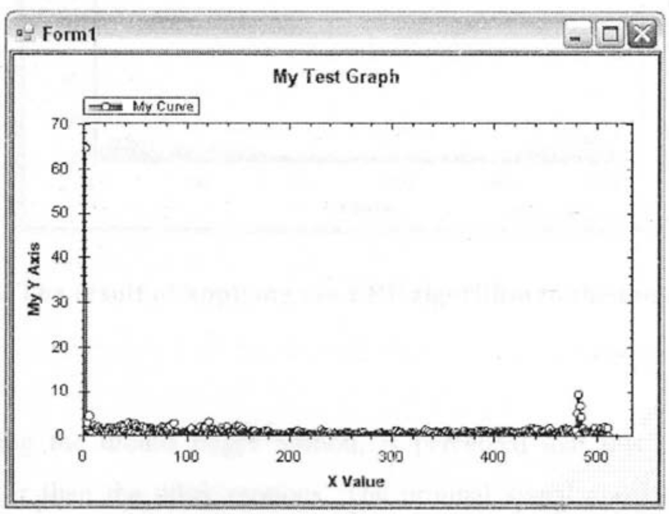

Figure 43. The result of applying the FFT algorithm to the index motion.

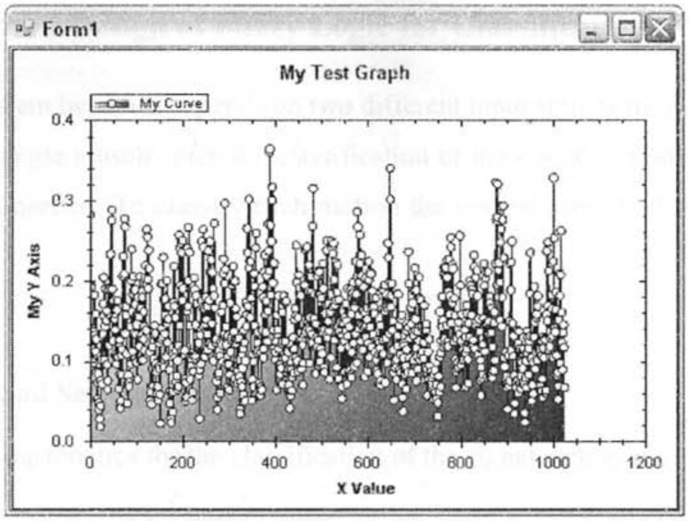

Figure 44. Thumb EMG input signal.

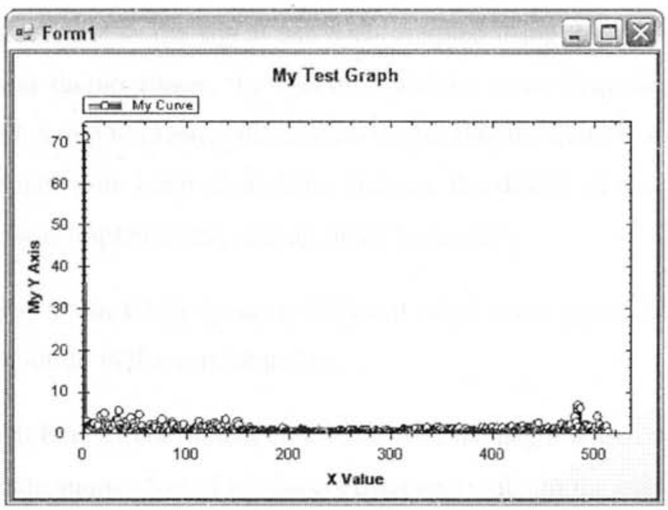

Figure 45. The result of applying the FFT algorithm to the thumb motion.

Regarding the thumb finger motion, is perceived that this EMG signal has amplitude higher than the other motions. The original signal and its FFT result are shown in Figure 44 and Figure 45.

3.2.2. Logic and Design of Fuzzy Logic for Classification

The system behavior depends on two different input signals from an EMG signal sampled on a single muscle, then the classification of the finger motions: index, middle and thumb are needed. To classify each motion the system uses an algorithm of fuzzy logic.

3.2.2.1. Rules and Sets Definition

The characteristics for the classification of the signal patters are:

- The summation of the FFT coefficients is the *Energy* of the EMG Signal.
- The number of times that the thresholds *MaxOS* have been reached.

The principal frequencies of the spectrum of the EMG signal is distributed along the low frequencies, and as the signal has been sampled using the same muscle for the index, middle and thumb finger, the spectrum and its main frequencies are the very similar. It is challenging to classify the motion by locating the main frequencies for each motion using ranges with crisp algorithms; instead, the design of a classification tool with fuzzy logic was implemented, adding fuzzy logic rules.

The energy of an EMG signal is different when noise signal has been sampled and when it is a motion in the current matrix.

Since each Fourier coefficient contribute with its magnitude to the resulting FFT Signal analysis, the summation of all the coefficients results in the Energy of the EMG Signal. This is the characteristic that allows us to classify between the types of motion at the same channel.

The rules for the fuzzy logic use the variable Alfa1 that is a numerical threshold with an adjustable value, and the manipulation of this variable also changes proportionally to the rest of Alfa's and Beta's values needed from the location of the Fuzzy Sets. The magnitude of *MaxOS* was set after managing different values for the threshold and in order to maximize the difference within the magnitudes and noise signals.

First it is necessary to obtain the *MaxOS* counter from the original sampled signal, then the *Energy* of the sampled signal is determined using the FFT algorithm. As the noise signal never overpasses the *MaxOS* threshold, if the value of *MaxOS* counter is less than 1, it means that the input signal sampled is a noise signal.

The thresholds for the magnitude of the motions may vary and to classify them using crisps sets is harder, since the incertitude level increases for each type of motion, using these levels with fuzzy logic result in the following ranges for each finger motion, in a scale from Alfa1 to Beta3, are:

- For the middle finger motion the magnitude of the Energy of the FFT is more than Alfa1 and less than Beta1.
- For the index finger motion the magnitude of the Energy of the FFT is more than Alfa2 and less than Beta2.
- For the thumb finger motion the magnitude of the Energy of the FFT is more than Alfa3 and less than Beta3.

The fuzzy logic rules are based in "if … then" heuristic conditionals, using the sentences mentioned above, the rules for the channel 1 of the controller are:

- If *Energy* < Threshold for Motion Energy then the output *y* is *Noise Signal*.

At this point if *Noise Signal* has been detected, then the algorithm restarts the system, and the sampling algorithm is turned on for obtaining a new input signal. Then if a motion is detected, the algorithm evaluation continues to the fuzzy logic classifier.

The fuzzy logic classifier system was developed in the MATLAB Fuzzy Logic Toolbox first, and later implemented in C# code with the rest of the algorithms. The platform consist in two input signals *EFFT* (*Energy*) and the *MaxOS* counter, one rule database, five fuzzy sets and one output that sends the output signal and calculates where the centroid of the weights has been found. The platform general view for the channel 1 is shown in Figure 46.

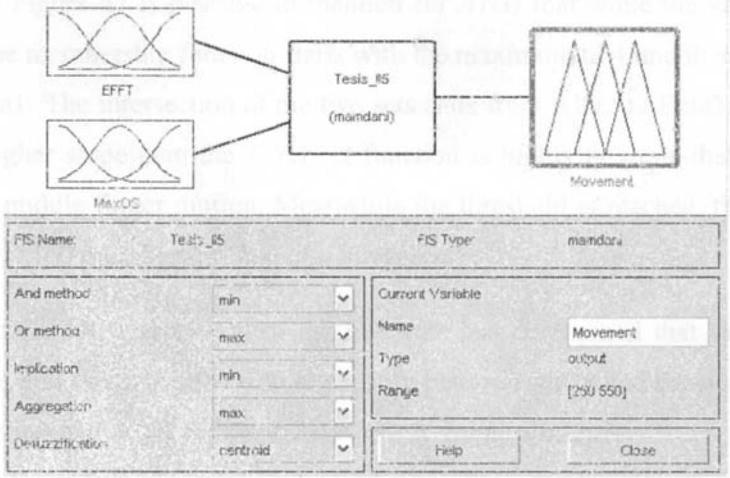

Figure 46. Fuzzy Logic System for the identification for a single channel.

The fuzzy logic system uses Mamdani method (max-min) [23], MATLAB automatically includes those parameters and the defuzzification method as centroid of gravity (COG) [23]. For this thesis the centroid was found using COA (center of average) with an algorithm in C#

Next, the input 1 which include the sets *A1(x)* and corresponds to the membership functions for middle, *A2(x)* for index, and *A3(x)* for thumb, is presented graphically in Figure 47.

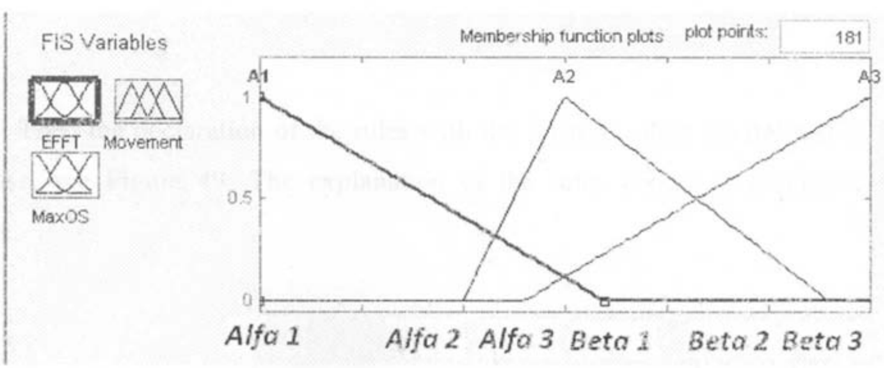

Figure 47. a) Set A1(x) that represent the membership function for the middle finger b) Set A2(x) index and A3(x) thumb.

From Figure 47 is possible to mention for *A1(x)* that while the value of *EFFT* increment, the membership function starts with the maximum of 1 and then decreases to 0 on x = Beta1. The intersection of the two sets stars from Alfa2 to Beta3, but as *A1(x)* presents a higher slope than the *A2(x)* set function is highly possible that the result is classified as middle finger motion. Meanwhile the threshold is reached, the *A1(x)* goes to 0 and then *A2(x)* membership function increases.

A second stage occurs when the first rule has determined that the output is a finger motion and continues the rule to classify between index and thumb, being *A2(x)* the index flexion and *A3(x)* the thumb flexion. A graphical representation for the A4(x) and A5(x) sets is shown in Figure 48.

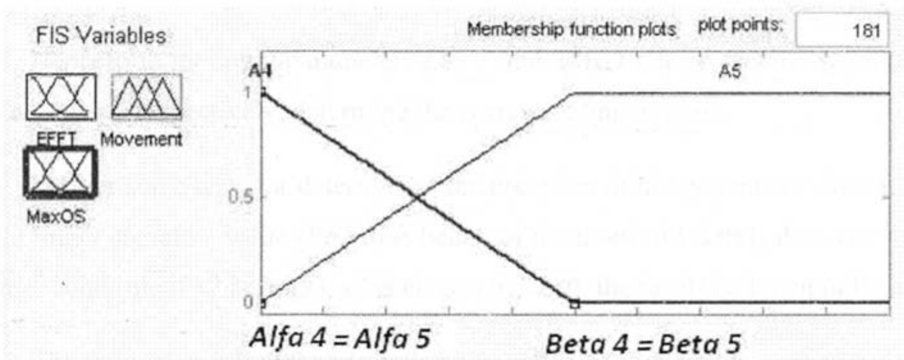

Figure 48. Input sets that helps to the fuzzy logic to classify between middle and index and thumb motions A4(x) for middle and A5(x) for the rest.

Then the declaration of the rules with the form if ...then are defined in the rule database, see Figure 49. The explanation of the rules chosen is explained in next section.

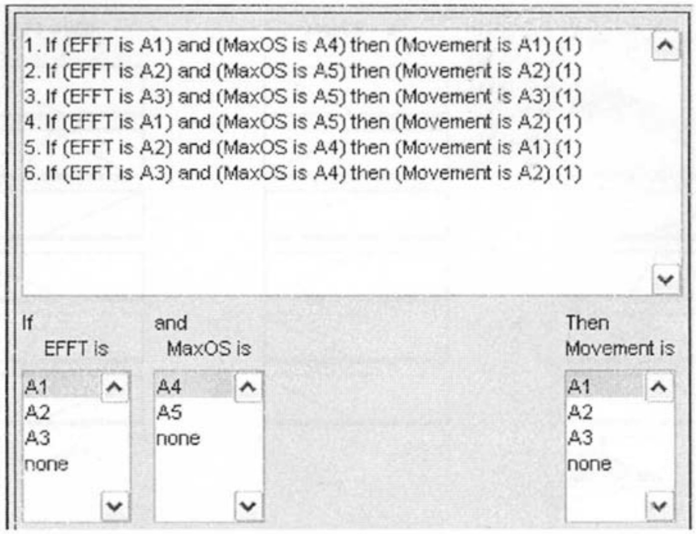

Figure 49. Rule Database for fuzzy logic classification.

Henceforth the input parameters *EFFT* and *MaxOS*: from now on we will name them $x1$ and $x2$, respectively, determine the corresponding motion.

Further some tests for determining the precision of the system are shown. First a middle finger signal $x1$ value (*EFFT*) is below of the threshold Beta1, then $x1$=300, and for the second rule if $x2$ is A4(x), $x2$ is chosen as $x2$=0, the result is shown in Figure 50.

The tests when $x1$=400 and $x2$=1 for an index flexion motion is shown at Figure 51 and finally to obtain a thumb finger motion $x1$=490 and $x2$=1 are presented in Figure 52.

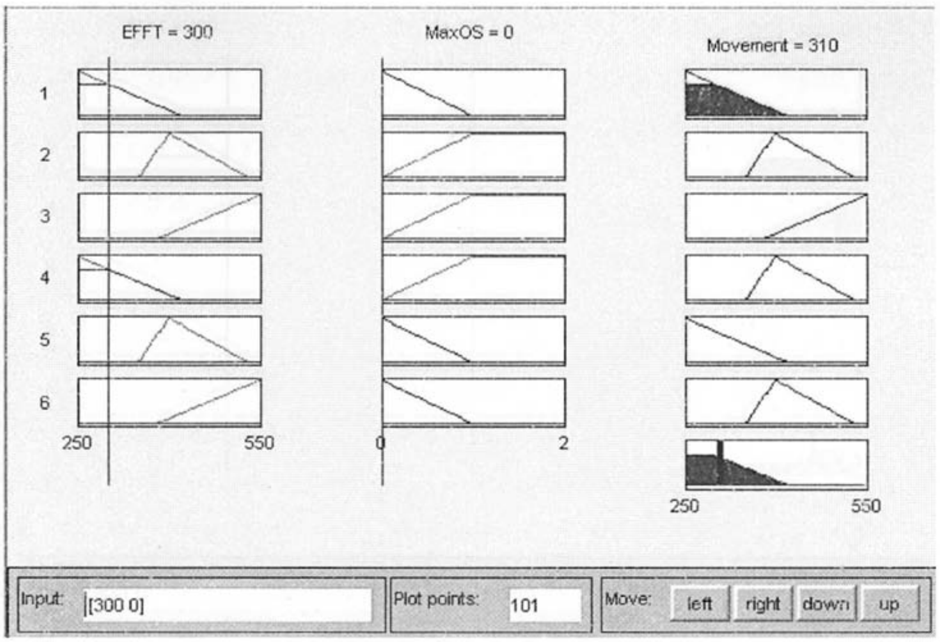

Figure 50. There is a motion and is middle finger motion.

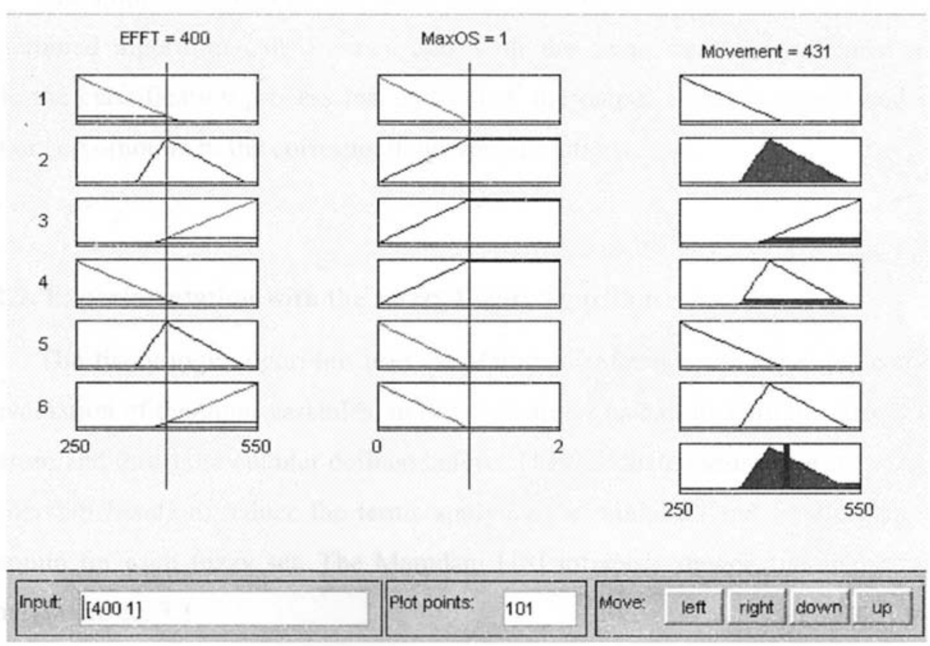

Figure 51. There is a motion and is an index finger motion.

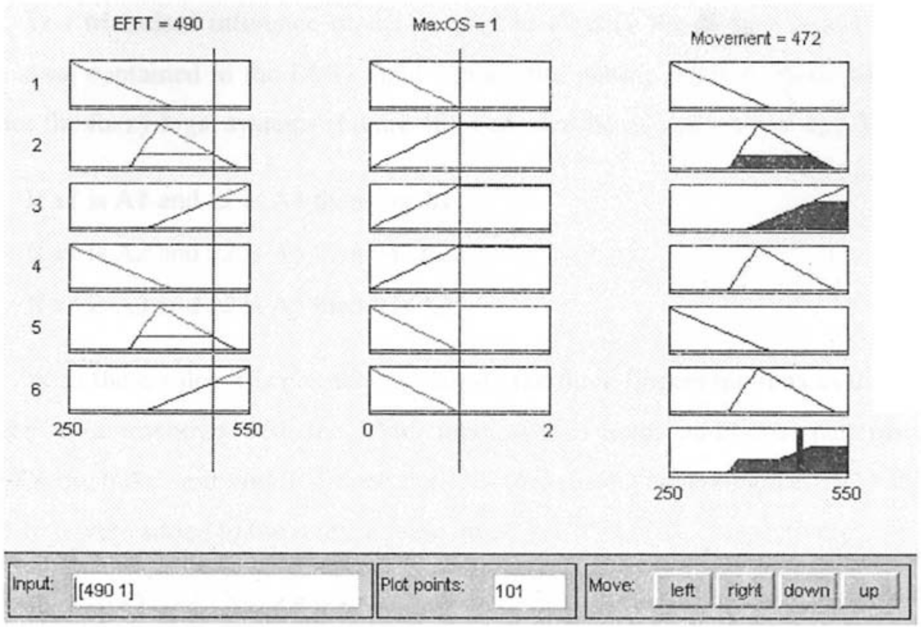

Figure 52. There is a motion and is a thumb finger motion.

The implementation of the fuzzy logic system in C# is a function of the main programmed algorithm called *Fuzzy_Sets* with the same structure presented above. While the classification process has concluded, the output signal is reproduced in the LED or servomotors to the corresponding type of motion.

3.2.2.2. Experimentation with the Fuzzy Logic Algorithm

The fuzzy logic algorithm uses de Mamdani inference model which consist in the evaluation of the input variables, in this case are *x1* and *x2* that are the energy of the spectrum and threshold counter defined before. Then evaluate these values to obtain the membership function, reduce the terms applying the minimum and finally getting the maximum for each fuzzy set. The Mamdani [18] inference model rule analytically is defined in the ec. 3.1.

$$\mu_{B'}(y) = max_{l=1}^{M}\left[min\left(\mu_{A_1^l}(x_1^*), \ldots, \mu_{A_n^l}(x_n^*), \mu_{B^l}(y)\right)\right] \tag{3.1}$$

The Mamdani inference model is used to classify the finger motion with the information contained in the EMG input signal after getting the two inputs values, the rules for the fuzzy logic systems (Figure 46), consider the rules from ec 3.2, 3.3 and 3.4.

- If *x1* is A1 and *x2* is A4 then *y* is A1. (3.2)
- If *x1* is A2 and *x2* is A5 then *y* is A2. (3.3)
- If *x1* is A3 and *x2* is A5 then *y* is A3. (3.4)

With these rules it is possible to classify the three fingers motions as the output, but after experimenting with the EMG input signals some additional patterns were found for the index and middle finger motions, then during analyzing the EMG signals. rules 3 to 6 were added to the rule database, in ec 3.5, 3.6 and 3.7 respectively.

- If *x1* is A1 and *x2* is A5 then *y* is A2. (3.5)
- If *x1* is A2 and *x2* is A4 then *y* is A1. (3.6)
- If *x1* is A3 and *x2* is A4 then *y* is A2. (3.7)

After a second epoch of experiments the system behavior increases with the new rule database. This non linear characteristic of the signal causes that input patterns may vary from the same finger motion, the above mentioned rules consider this, even when the input signal EMG has a spectrum with energy that corresponds to a middle motion, if the amplitude of the original signal reaches the *MaxOS* threshold this means that the input EMG is a pattern more similar to a index motion than a middle motion. Using a similar logic it is possible to explain the fifth rule that is, even when the input signal EMG has a spectrum with energy that corresponds to a thumb motion, if the amplitude of the original signal does not reach the *MaxOS* threshold this means that the input EMG is a pattern more similar to an index motion than a thumb, because there is no case where thumb motion did not reach the threshold.

Let consider the following example, using the parameters for the fuzzy logic system design shown in ecs 3.8 and 3.9.

- Alfa1 = 250, Alfa2 = 350, Alfa 3 = 380. (3.8)
- Beta1 = 420, Beta2 = 530, Beta3 = 550. (3.9)

If the input signal has the parameters of the Figure 50, when $x1$=300 and $x2$ = 0 and we use the Mamdani inference model, then substituting the defined parameters for the fuzzy logic system design using the 4.3.2.1 section functions for the fuzzy sets. The output is derived from the evaluation of the variables from the membership functions of the Fuzzy Sets:

- A1x1 is the result of evaluating $x1$ in fuzzy set A1.
- A2x1 is the result of evaluating $x1$ in fuzzy set A2.
- A3x1 is the result of evaluating $x1$ in fuzzy set A3.
- A4x2 is the result of evaluating $x2$ in fuzzy set A4.
- A5x2 is the result of evaluating $x2$ in fuzzy set A5.

The ecs 3.10,3.11 and 3.12 are the three membership functions for each fuzzy set:

$$A_1(x) = \begin{cases} \dfrac{Beta1 - x}{Beta1 - Alfa1} & x < Beta1 \\ 0 & x \geq Beta1 \end{cases} \tag{3.10}$$

$$A_3(x) = \begin{cases} 0 & x < Alfa3 \\ \dfrac{x - Alfa3}{Beta3 - Alfa3} & x \geq Alfa3 \end{cases} \tag{3.11}$$

$$A_2(x) = \begin{cases} 0 & x < Alfa2 \\ \dfrac{x - Alfa2}{y2 - Alfa2} & Alfa2 \leq x < y2 \\ \dfrac{Beta2 - x}{Beta2 - y2} & y2 \leq x < Beta2 \\ 0 & x \geq Beta2 \end{cases} \tag{3.12}$$

Then Mamdani inference model is used to obtain the weights for the current input signal, then evaluate in ec 3.1 and the result is shown in ec 3.13.

$\mu_{B'}(y)$ = max[min(A1x1, A4x2, $\mu_{A1}(y)$), min(A2x1, A5x2, $\mu_{A2}(y)$),
minA3x1,A5x2,μA3(y) minA2x1,A4x2,μA1(y) minA3x1,A4x2,μA2(y)

μ_(B^') (y) = max[min(0.705,1, μ_A1 (y)), min(0,0, μ_A2 (y)),
min(0,0, μ_A3 (y)) min(0,1, μ_A1 (y)) min(0,1, μ_A2 (y))]

$\mu\_(B\hat{}') \ (y) = max[(0.705, \mu\_A1(y)); (0, \mu\_A2 \ (y)),$
$(0, \mu\_A3(y)); (0, \mu\_A1(y)); (0, \mu\_A2(y))]$

$$\mu\_(B\hat{}') \ (y) = [\ 0.705, \mu_{A1}(y);\ 0, \mu_{A2}(y);\ 0, \mu\_A3 \ (y)\ ] \qquad (3.13)$$

The resulting inference (7) consist in the variables *w1*, *w2* and *w3*, these are used to obtain the COA, center of average of the actual inference. The COG that uses MATLAB is more complicated to evaluate, so in this research the COA is used (see ec. 3.14).

$$y^* = \frac{w1*y1+w2*y2+w3*y3}{w1+w2+w3} \qquad (3.14)$$

The parameters *y1*, *y2* and *y3* are defined from the fuzzy sets design where:

- *y1* = Alfa1 = 250
- *y3* = Alfa3 = 550
- *y2* = 400

Then the y^* is solved using ec. 3.14, where the output for the EMG sampled with values *x1*=300 and *x2*=0 is obtained.

$$y^* = \frac{0.0705 * 250 + 0 * 400 + 0 * 550}{0.705 + 0 + 0}$$

$$y^* = 250$$

This means that the EMG signal was a middle finger motion; the system output for this case is show in Figure 53.

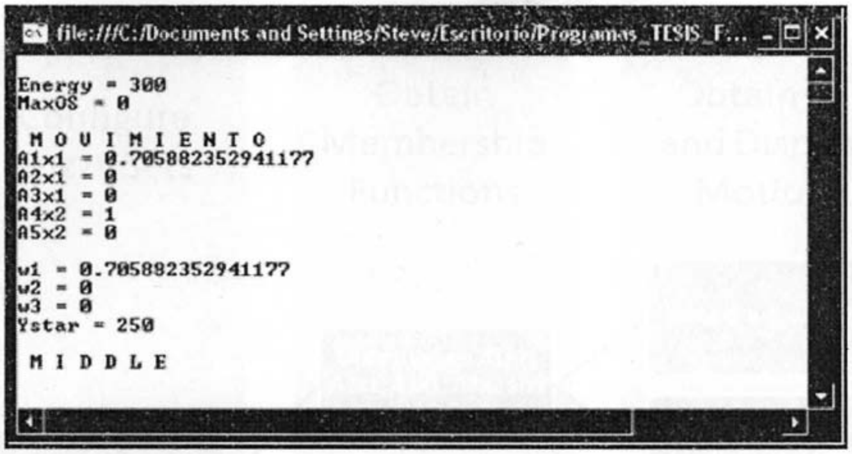

Figure 53. Fuzzy logic classifying the output for x1=300, x2=0.

The output using the same inputs *x1* and *x2* with MATLAB (see Figure 50) is considerably different (y* = 310) from the calculation using COA (y* = 250), but the performance of the COA algorithm is valid to be considered as the output method to obtain the finger motion of this system.

Figure 54 shows the procedure of the algorithm used to classify the sampled EMG signal by the fuzzy logic classification.

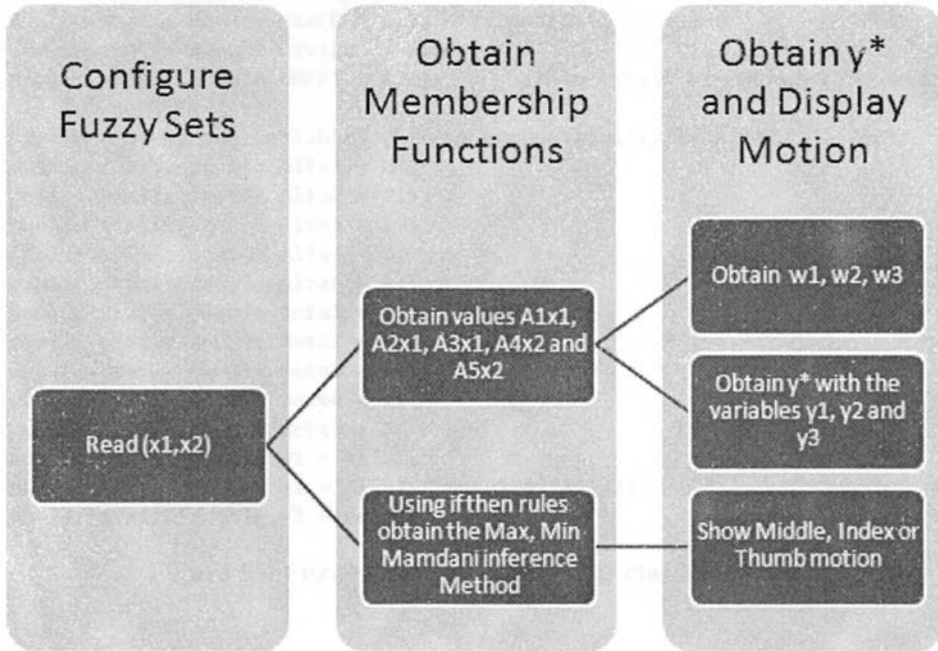

Figure 54. Fuzzy logic classification algorithm.

The Figure 55 show the parameters for the configuration of the fuzzy logic identifier algorithm, these parameters can be adjusted and depend only on the input value Alfa1. Figure 56 shows an overview of the structure of the identification system code. The main purpose of doing the fuzzy logic parameters adjustable is because as EMG signals are non linear signals depend on the patient, and electrode locations may vary for the same person in different days, then the system can be configured by adjusting the variables.

```
// THRESHOLD SINTONIZACION
public static double MaxCO = 0.3;    // Original Signal
public static double Divisor = 1150;
public static double UMFFT = 170;        // Threshold btw Noise & Movement

// The rest of the variables changes proportionally to Alfa1
public static double Alfa1 = UMFFT;
public static double Alfa2 = 215;
public static double Alfa3 = 285;
public static double Alfa4 = 0;
public static double Alfa5 = 0;
public static double Beta1 = 230;
public static double Beta2 = 290;
public static double Beta3 = 400;
public static double Beta4 = 1;
public static double Beta5 = 1;
public static double y1 = Alfa1;
public static double y2 = Alfa2+((Beta2-Alfa2)/2);
public static double y3 = Beta3;
```

Figure 55. Fuzzy logic parameters for classification.

```
// Evalue the centroid using the COA method
double ystar = 0;
double Movimiento = 0;
ystar = ((w1 * y1 + w2 * y2 + w3 * y3) / (w1 + w2 + w3));
if (w1 > w2){
    if (w1 > w3){
        Movimiento = 1;}
}  // si Mov = 1 then Medio
if (w2 > w1){
    if (w2 > w3){
        Movimiento = 2;}
} // si Mov = 2 then Indice
if (w3 > w1){
    if (w3 > w2){
        Movimiento = 3;}
} // si Mov = 3 then Pulgar
SetValues[0] = w1;
SetValues[1] = w2;
SetValues[2] = w3;
SetValues[3] = ystar;
SetValues[4] = Movimiento;
return SetValues;
```

Figure 56. Fuzzy logic algorithm implemented in C#.

3.2.2.3. Configuration of the System Parameters

The input EMG signals may vary on its main characteristics for different users, and also for the same user, so it is necessary to tune the parameters of the system to get a satisfactory performance. This is a mandatory procedure every time that the EMG monitoring system will be used.

This section presents a list of considerations to obtain approximate values for the fuzzy logic and other system parameters.

- First, sample a set of input signals containing noise, middle, index and thumb motions, and manipulate the values of *MaxCO* (which is the threshold that identifies between the motions) and UMFFT (which is the threshold between noise and motion).
- Next, the following values of the design parameters of the fuzzy logic identification must be defined with an approximation, see Figure 55.
- Then, verify the system behavior according to the next recommendations
    - If the system is able to distinguish between noise and any motion, then the *UMFFT* parameter was correctly defined.
    - If the system fits the last point but it is not able to distinguish between middle and index-thumb motions, then minimize the parameter *MaxCO* until better performance is achieved.
    - If the system fits the last point but is not able to distinguish between index and thumb motions, then reduce the parameters Beta2 and Alfa3 from the fuzzy logic algorithm (Figure 55) until this conditions is reached.
- Finally to get an optimum best performance, it is necessary to standardize the motion type from the user, i.e. try to reproduce for each type of motion the invoking motion, in order to train the system for the identification for a new user.

Chapter 4
Experimental Work

Once the system classified correctly the motion contained in the current EMG signal, the system emits an output voltage signal from the ports DA3, DA4 and DA5 of the FEZ Panda II.

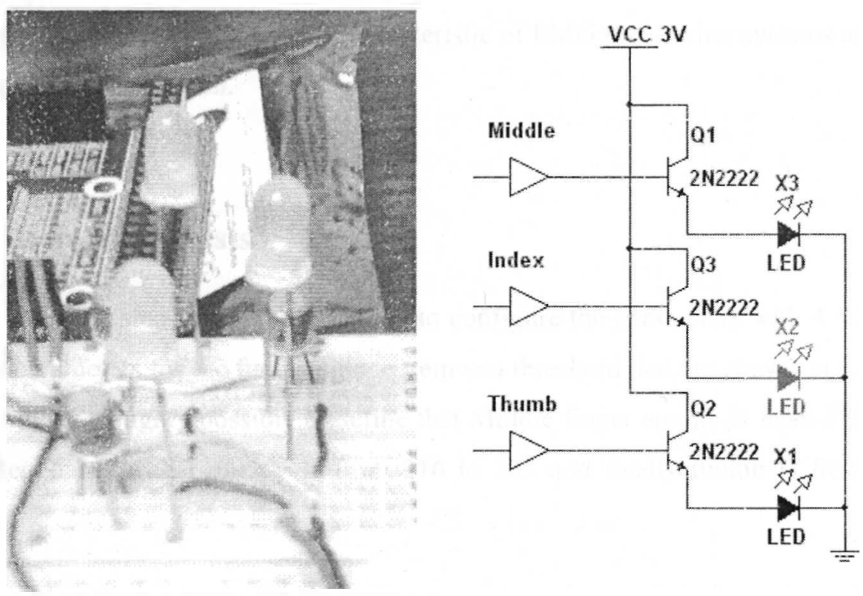

Figure 57. LED's designated for each type of motion.

The maximum voltage that the FEZ digital output port supported is lower than 3.3 Volts when the output is enabled, an additional voltage source of 5 Volts is connected to the Collector pin, then the digital output ports, are used to control the Base pin of a 2N222 NPN Transistor, then, when the system classifies the current EMG input signal as a finger motion, the Base is polarized; the voltage flows through Collector to Emitter and finally to the LED designated to the respective degree of freedom. Figure 57 shows the LED output from the FEZ and the electronic schematic.

4.1. Test and Validation

Nowadays there are many commercial systems that use EMG's as control signal. The main characteristic from these systems is that all systems has a percentage of correct identification, this is because of the EMG signal is stochastic, and then the patterns are difficult to classify, from [1] the average of the EMG commercial systems that uses one single channel to classify one single motion is lower than 87 . This research uses one single channel to classify three motions. Furthermore the importance of identifying correctly is the main characteristic of EMG monitoring systems as the one developed in this research.

4.1.1. Simulation Tests

The first step to use the system is to configure the parameters with 4.3.2.2, then test the parameters for the fuzzy logic system and threshold that are shown in Figure 55. From this it is roughly possible to define that Middle finger energy is from 170 to near 215, then Index finger energy is from 216 to 285 and finally thumb is from 290 to Beta3.

The system is ready for the testing process, and consists in having a stable input EMG signal whit a relaxation position (see Figure 27), simulate an input signal with $x1$ = 170 and $x2$ = 0. If the system is configured correctly then the result must be a middle finger motion, see Figure 58.

Figure 58. Simulation of a middle finger motion.

Is possible to determine that the membership function of $A1x1$=1, and that $A4x2$ = 1, because *MaxOS* is 0. The value of $x1$ = 170 was in purpose because is the same value of *Alfa1* ad then the result must be a middle finger motion.

At this point, the system is able to determine correctly between noise and medium finger motion.

The next test consists in simulating an Index finger motion, the same form as the last test, the values are chosen for $x1$ and $x2$, 252.5 and 1 respectively. Note that, as the maximum value in the membership function of the second fuzzy set is $y2 = x1$ and as the threshold has been chosen $MaxOS = 1$, the correct answer must be an index finger motion; the result of the simulation is shown in Figure 59.

Figure 59. Simulation of an index finger motion.

The system is able to correctly classified the simulated input as an index motion. The next step it so simulate a thumb finger motion, since the maximum value in the membership function of the third fuzzy set is *y3*, then this value is the input *x1* and as the threshold has been chosen *MaxOS = 1*, the correct answer must be a thumb finger motion. The result of the simulation is shown in Figure 60.

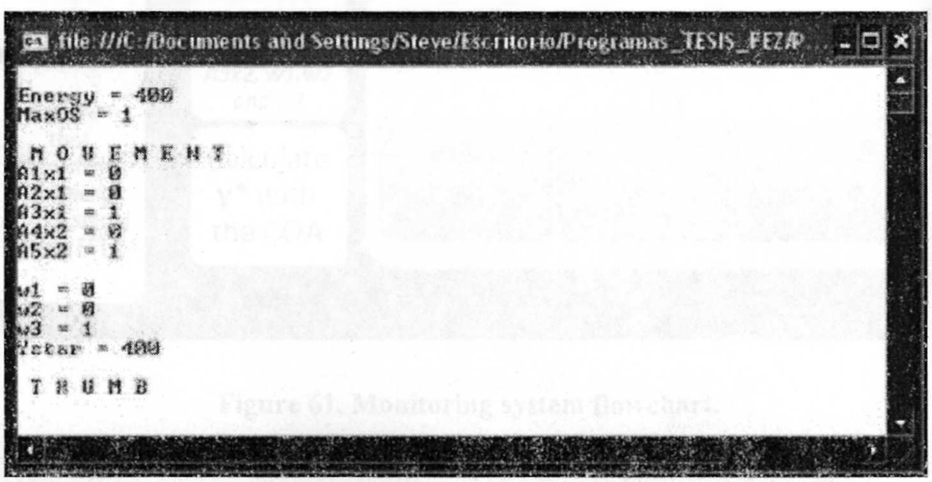

Figure 60. Simulation of a thumb finger motion.

The values $A3x1$, $A5x2$, were expected to be 1 and the output y is 400 which means that the output is actually a thumb finger motion. It is concluded that the system correctly identifies the simulated values and the next step is to test the system online.

4.1.2. Online Tests

The online testing is a procedure where the algorithm must classify when there is a motion and if the current signal is noise then a "while" cycle keeps sampling until the motion is detected. The Figure 61 shows in a flowchart how the process in which the system performs the online testing.

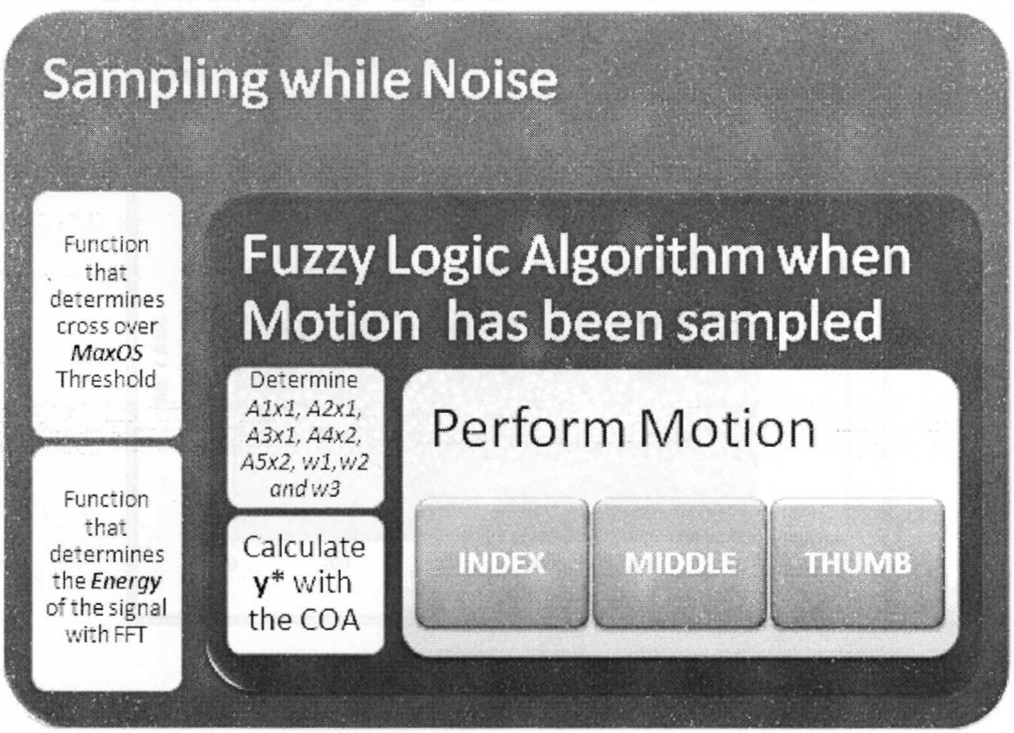

Figure 61. Monitoring system flowchart.

The main differences between online test and simulation is that EMG input signals must be adjusted to fits the system parameters, then the system performs the identified motion that is nearest of the motion defined from the fuzzy rules.

The first online test consists in sampling each type of input signal that is: (i) noise, (ii) middle, (iii) index, and (iv) thumb, and then calculate if the system is able to classify it.

For the noise input signal the energy below of a threshold *UMFFT* = 170, then the system continue sampling until a motion is detected. From the Figure 62 and 63 is possible to see that the sampled signal has no coefficient greater than the threshold *MaxOS* = 0.3, which is the value of *x2* and although this affirmation allows to define the current signal as noise, the threshold which defines if there is motion or not is the *UMFFT* and then the fuzzy logic algorithm for identification never starts.

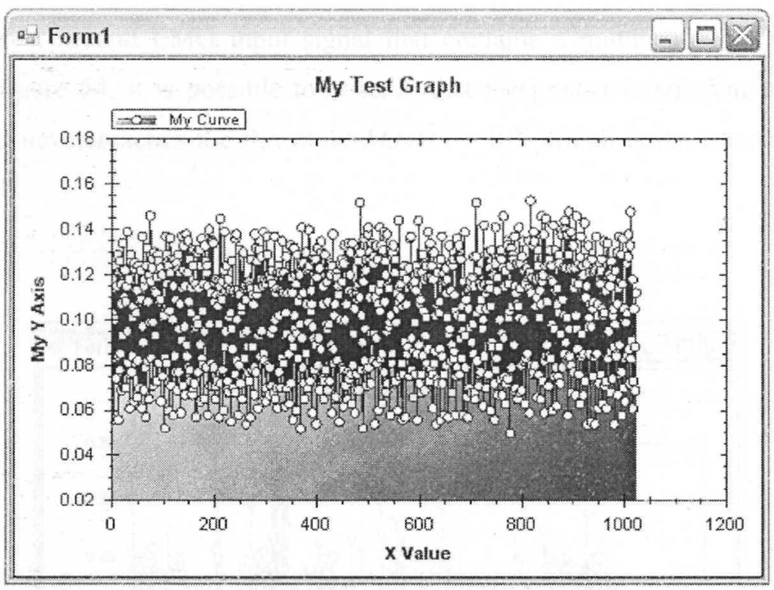

Figure 62. Online noise input signal.

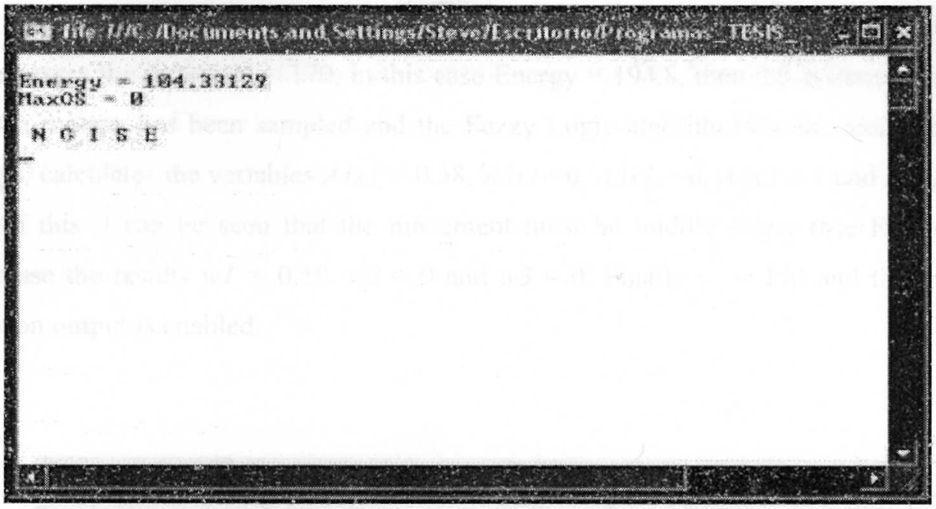

Figure 63. Response of the system with online noise input signal

Then a second EMG input signal that contains a middle motion is sampled. From the Figure 64, it is possible to observe that the greater coefficient in the EMG input signal never reaches the threshold *MaxOS* = 0.3, which is the same case of the noise signal.

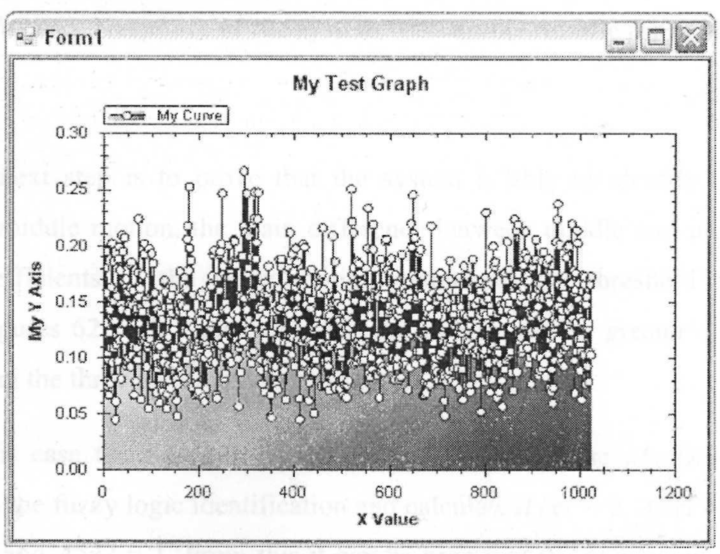

Figure 64. Online middle finger motion in the input signal.

The difference between noise and middle finger motion is that the Energy overpasses the threshold = 170, in this case Energy = 194.8, then the system identifies that a motion has been sampled and the Fuzzy Logic algorithm for the identification starts, calculates the variables $A1x1$ = 0.58, $A2x1$= 0, $A3x1$ = 0, $A4x2$ = 1 and $A5x2$ = 0. From this it can be seen that the movement must be middle finger (see Figure 65) because the results $w1$ = 0.59, $w2$ = 0 and $w3$ = 0. Finally y = 170 and the middle motion output is enabled.

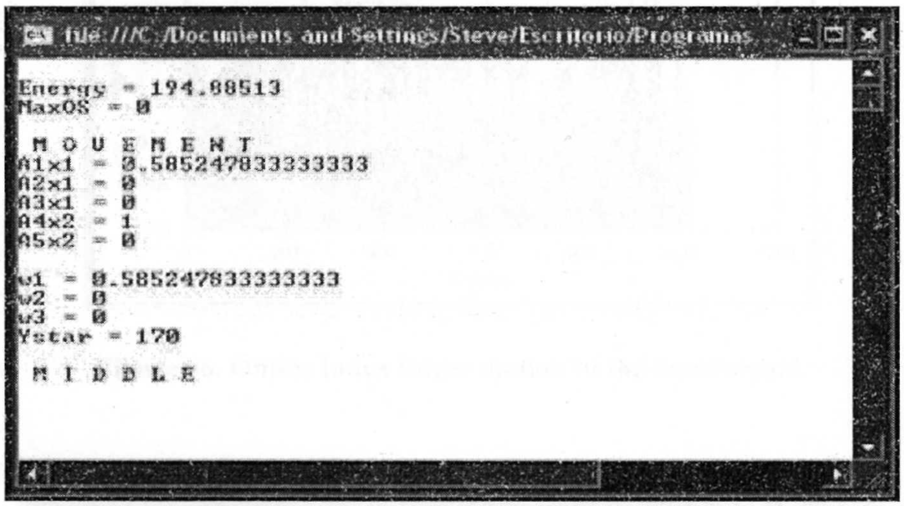

Figure 65. Response of the system with online middle input signal.

The next step is to prove that the system is able to identify between index motion and middle motion, the main difference between middle and index motions is that the coefficients of the index motion overpasses the threshold $MaxOS$ = 0.3 (compare Figures 62 with Figure 64), and the Energy can be greater or not, this was adjusted using the three additional rules from 4.3.2.2.

In this case the Energy of the signal is 271.2 and the $MaxOS$ = 1, then the algorithm do the fuzzy logic identification and calculate $A1x1$ = 0, $A2x1$= 0.501, $A3x1$ = 0, $A4x2$ = 0 and $A5x2$ = 1. From this it can be seen that the movement must be index (see Figure 66, 67) motion because the resulting $w1 = 0$, $w2 = 0.501$ and $w3 = 0$. Finally $y = 252.5$ and the middle motion output is enabled.

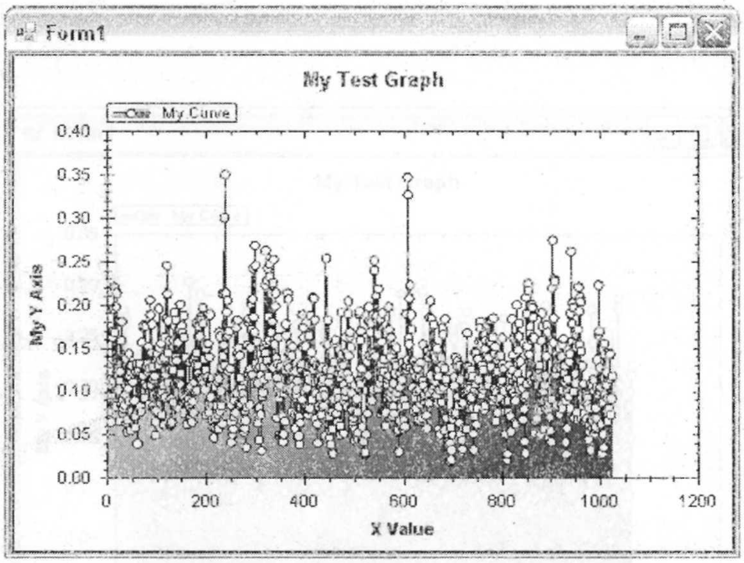

Figure 66. Online index finger motion in the input signal.

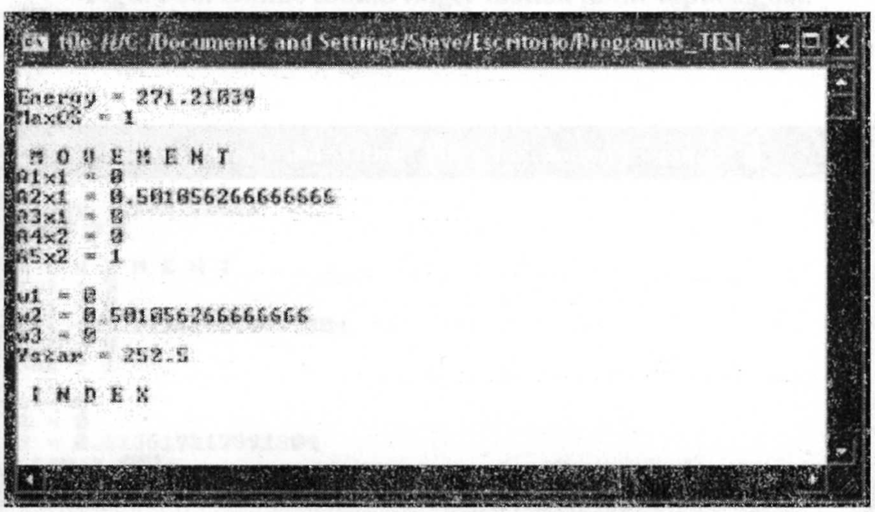

Figure 67. Response of the system with online index input signal.

Finally, a thumb motion signal is sampled. The differences between middle and thumb motion is that thumb overpass the *MaxOS* threshold and also that the Energy is greater, meanwhile the only difference between thumb and index is just the magnitude of the Energy. The evaluation of thumb motion is shown in Figures 68 and 69.

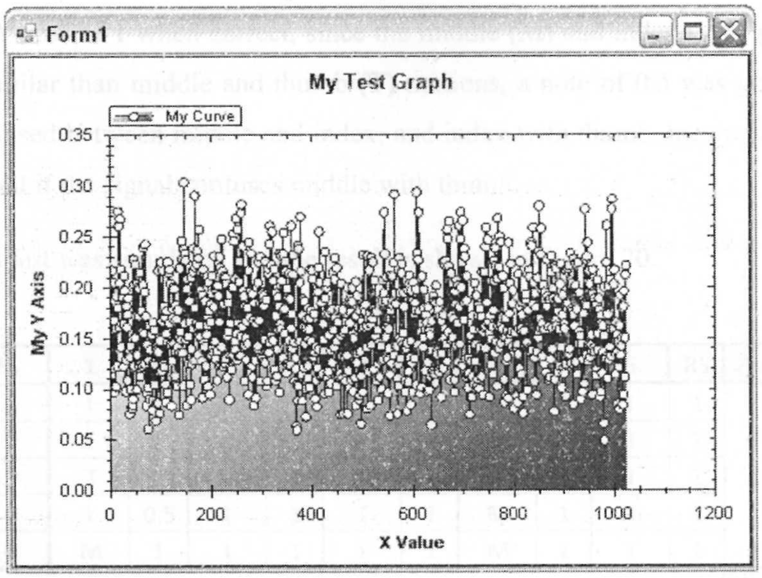

Figure 68. Online thumb finger motion in the input signal.

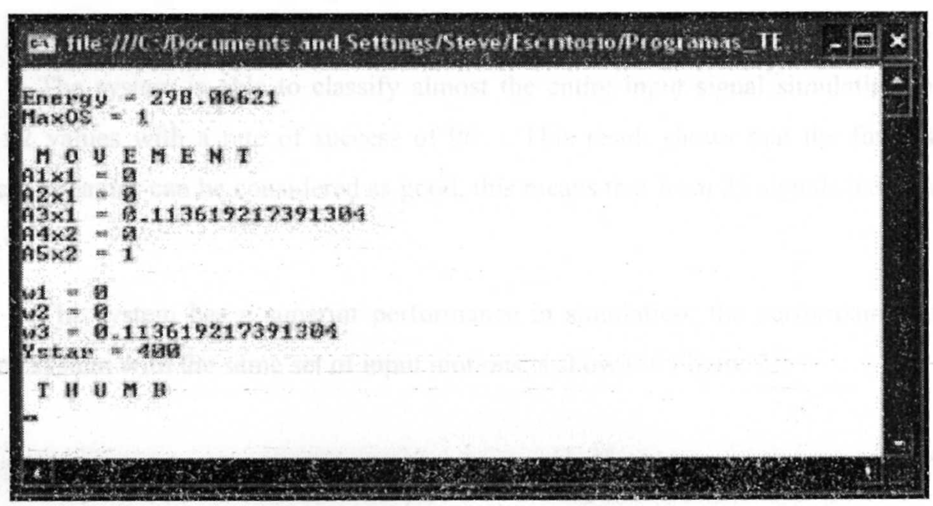

Figure 69. Response of the system with online thumb input signal.

4.1.3. Validation Tests

Although the system is able to identify between noise and movement in range of 9 to 10 motions, this percentage of success rate between motions decreases. To obtain this value the following test was performed.

A set of 5 motions were defined and for each motion a qualification was conferred. A note of 1 when correct, since the middle (M) and index (I) finger motions are more similar than middle and thumb (T) motions, a note of 0.5 was granted if the system confused between middle and index, and index with thumb, meanwhile a 0 note was conferred if the signal confuses middle with thumb.

This test was simulated and the result is shown in Figure 70.

TESTS	1	R1	2	R2	3	R3	4	R4	5	R5	Average
Set 1	I	1	M	1	T	1	T	1	I	1	100.00%
Set 2	I	1	M	1	T	1	M	1	T	1	100.00%
Set 3	T	1	M	1	M	1	T	1	I	1	100.00%
Set 4	I	0.5	I	1	T	1	M	1	M	1	80.00%
Set 5	M	1	I	1	I	1	M	1	T	1	100.00%
											96.00%

Figure 70. Testing the monitoring system, simulating the x1 and x2 values.

The system is able to classify almost the entire input signal simulating the x1 and x2 values with a rate of success of 96 . This result shows that the fuzzy logic system behavior can be considered as good, this means that from 25 signals has an error of 1.

The system has a superior performance in simulation; the performance of the online system with the same set of input motions is shown in Figure 71.

TESTS	1	R1	2	R2	3	R3	4	R4	5	R5	Average
Set 1	I	1	M	1	T	0.5	T	1	I	0.5	60.00%
Set 2	I	0.5	M	1	T	1	M	0.5	T	1	60.00%
Set 3	T	1	M	0.5	M	1	T	1	I	1	80.00%
Set 4	I	1	I	1	T	1	M	0.5	M	1	80.00%
Set 5	M	0.5	I	1	I	1	M	1	T	1	80.00%
											72.00%

Figure 71. Testing the monitoring system, performing an online test.

From the Figure 71, it can be seen that the system classification success decreases in comparison with the rate of success from the simulation from 96 to 72 . Although this can be misunderstood, from [1] it is possible to determine that the success rate of the system is near the top level. Also it can be seen that none of the motions not identified between middle and thumb motion, this means that when an middle motion was the desired output motion, the system does not acknowledge with the upper motion and the index, or the same case when thumb motion was the desired motion the system with the lower that is index, this case occurs 7 from 25 cases, then the rate of success obtained was 72 , which is an acceptable system behavior for an online EMG monitoring system.

Chapter 5
Conclusions and Further Work

The development of this thesis required a thorough analysis of EMG signals from its origin in the human body to the understanding of the acquisition process, which varies greatly for the same person and even during measurement.

5.1 Conclusions

The EMG signal is originated within the muscle and they are affected by events such as stress or tension caused by external factors these factors can be expressed in the limb to be measured, even if also due to periods of experimentation are of time.

Because of this feature of the EMG, that it is a time-varying signal, demanded more time on the analysis to understand the different ways that the EMG signal can occur for the same movement with different electrode locations. The process of experimentation resulted in the use of an different method and so far not found in the literature; which recommends at a distance of electrode placement no more than 1 cm, but for this research, the electrodes are located over a muscle, separated by a distance of approximately 12 cm.

Due to the previously mentioned placement of the electrodes, it was possible to meet one of the main objectives of the research, which refers to the acquisition of EMG signals corresponding to various movements using a single channel. This contribution is very important since in previous works of monitoring EMG signals a sampling channel for a single movement or type of motion is used. This means that using the methodology proposed in this research, there is only need for a single acquisition system and three electrodes to detect 4 states, which are the index, middle, thumb finger motions and also includes the noise signal as a fourth state, since it also needs to be discriminated and that corresponds to the idle state.

When considering the use of traditional methods of a channel for each degree of freedom, an interface as shown in 3.2.1 is built. Which in this case 3 channels and a total of 7 to 9 electrodes for all types of motion and result in less comfort for the user, increasing the hardware cost up to three times, the computational cost would increase as the classifier algorithms eventually grows in complexity, due to the space that requires a great number of electrodes provided in the forearm. This alternative may not be possible of locating of a large number of surface electrodes in the same limb.

Because the signals comes from the same muscle, using the signal spectrum obtained by FFT analysis resulted in a feature that provided a proper performance for motion classification, in addition, the algorithm relied classification uses as a second parameter of threshold crossing. It is noteworthy that initially it had been considered sufficient to use a DFT algorithm, which delivers the same result as FFT, however when the online implementation of the system begins, it was observed that the signal processing took about 30 to 40 seconds, which made this system as a non viable alternative because of the slow processing, and it was then decided to develop the FFT algorithm, which reduced the processing in a large form, that is, reduced to a time less than 2 seconds for processing and display of results.

The proposal to use a classifier using fuzzy logic algorithm favored the process of identifying signals. This methodology can be implemented easily once you have an expert knowledge of the system, as well as the design parameters of the fuzzy classifier depends only on the definition of the rules of the Alfa and Beta variables, and thus the configuration of the monitoring system for a new user is given easier, that how it would be using only the energy variable amplitude and zero crossing with crisp methods.

It is worth mentioning that the performance of 72% is considered acceptable result, since the characteristics of the EMG are difficult to map and this research presents an average behavior within the currently carried out procedures, which even using commercial monitoring systems. It also has the advantage that the algorithms were developed using open source, allowing its implementation and development, making the system a free tool.

As an added value to the system is the feature of portability, which makes it possible to mount the system on the device that will require the EMG signal as a control signal and only need a 9-volt battery, both to feed the circuit and the card processing, making the system a viable tool for continuous development and cost reduction.

Finally, it is possible to conclude that although the nature of the EMG signal is highly variable can be considered a good signal for controlling, due to its ease of acquisition and instrumentation required is readily available. Although can be a disadvantage the need for processing complex algorithms, there are already many tools such as artificial intelligence, in addition there is spectral analysis by Fourier and wavelet transforms for better understanding and expansion of its applications in new fields of engineering .

5.1 Further Work

The system is able to classify between 4 stages that includes the three motions, using a single actuator to perform the flexion motion of the corresponding degree of freedom. An approach of a servomotor control using a fuzzy logic controller is presented. Once the system proposed in this thesis had classified the EMG signal as motion, the output enables the control system that corresponds to the degree of freedom of the exoskeleton. The block diagram of the servo motor controller is shown in figure 72.

The fuzzy logic controller uses the error and the error derivative to manipulate the plant, in this case the plant is the servo motor dynamics. The set point which is the desired angular positions is chosen as 120, but this depends on the angle that the servomotor needs to perform correctly the motion of the exoskeleton.

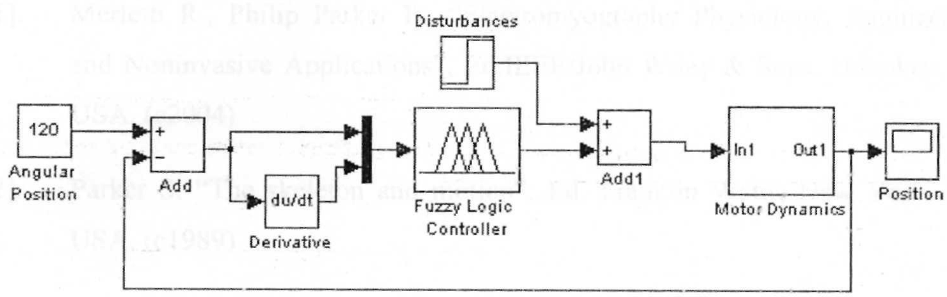

Figure 72. Block diagram of a servomotor control system.

A second further work proposed is the implementation of the memory algorithm that was performed in this research but was not included in the thesis content, although in simulation it has a satisfactory behavior, at online test the system had none expected responses.

Finally, a third suggested further work is to implement an algorithm of auto configuration for the fuzzy logic classifier, using methods as genetic algorithms the fuzzy sets can be adjusted easier than the method proposed in chapter 3.3.2.3. This may increase the classifier performance.

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