VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ
BRNO UNIVERSITY OF TECHNOLOGY

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ANALÝZA EMG SIGNÁLU PRO PROTETICKOU RUKU ZALOŽENOU NA FUZZY LOGICE

ANALYSIS OF EMG SIGNAL FOR PROSTHETIC HAND BASED ON FUZZY LOGIC TECHNIQUE

BAKALÁŘSKÁ PRÁCE
BACHELOR'S THESIS

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BRNO, 2008

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Analýza EMG signálu pro protetickou ruku založenou na fuzzy logice

Abstrakt

Lidská ruka je koncový orgán horní končetiny, který slouží k důležité funkci uchopení, stejně jako důležitý orgán pro vnímání a komunikaci. Je to úžasný příklad o tom, jak komplexní mechanismus může být implementovaný, schopný chápat velice komplexní a užitečné úkoly používáním velmi efektivní kombinace mechanismů, snímání a řídicích funkcí.

Elektromyogram (EMG) byl původně vyvinutý pro vyšetrování svalnatého nepořádku. Klinické aplikace se brzo rozšířila, nejpozoruhodněji ve výzkumu epilepsii a nakonec se stal populární po zavedení protéz, specificky tělem poháněných protéz. EMG nahrávání je použito pro studování funkčního stavu svalu během různých pohybů. Cílem tohoto projektu je vyvinutí elektromyogramové (EMG) metody třídění, která bude pomáhat v aplikacích jako systém pracující v reálném čase.

První část tohoto projektu bylo získávání informací. Údaje reálného času byly zaznamenaný pomocí EMG monitorovacího systému (BIOPAC) a kompletní datová sada různých osob byl zaznamena. Tyto EMG data byly konvertované ze souboru ASCII do čitelné formy pro MATLAB.

Druhou částí projektu byla extrakce vlastností. Pět tradičních parametrických rysů bylo vypočítáno, jmenovitě Integrovaný EMG (IEMG), variance (VAR), Zero Crossing (ZC), Slope Sign Changes (SSC) a Vlnová délka (WL).

Třetí část projektu byla klasifikace EMG vzorů s použitím fuzzy logiky. Výsledky jsou docela slibné.

Klíčová slova

Elektromyograf (EMG), protetická ruka, Biopac Student Lab, akční potenciál (AP), motor unit action potential (MUAP), elektrody, svaly, Self-Organizing Feature Map (SOFM), Zero-crossing (ZC), threshold, variation, Fuzzy logic, Fuzzy Inference System (FIS), Mamdani type FIS

Analysis of EMG signal for prosthetic hand based on fuzzy logic technique

Abstract

The human hand is an important limb essential for movement, grasping, perception , as well as being a vital part of the human body for sensation and communication. It is a classic example of how a complex mechanism can be implemented, capable of realizing very tedious and useful tasks using a very effective combination of mechanisms, sensing, actuation and control functions.

Electrmyogram (EMG) was originally developed for the detection and further correction of muscular disorder. Further applications were soon evident, most importantly in epilepsy, and finally it became popular due to the introduction of prosthetics, specifically body powered prosthesis. EMG recording is used for studying the functional state of the muscle undr various motions when it undegoes stress and tension. The goal of this project is to develop electromyogram (EMG) classification methods that shall help in applications like real-time system.

First Phase of this project was Data Acquisition. Real time data using PC based EMG Monitoring System (BIOPAC) was recorded and a complete data set of different subjects was obtained. This EMG data was converted from ASCII file to a readable form for MATLAB.

Second Phase of this project was Feature Extraction. Five traditional parametric features, namely Integrated EMG (IEMG), Variance (VAR), Zero Crossings (ZC), Slope Sign Changes (SSC) and Waveform Length (WL) were extracted.

Third phase of this project was Classification of EMG patterns using fuzzy logic techniques. The results were quite promising.

Keywords

Electromyogram (EMG), prosthetic hand, Biopac Student Lab, Action Potential (AP), Motor Unit Action Potential (MUAP), electrodes, muscles, Self-Organizing Feature Map (SOFM), Zero-crossing (ZC), threshold, variation, Fuzzy logic, Fuzzy Inference System (FIS), Mamdani type FIS

Bibliografická citace

OLLÉ, T. *Analysis of EMG signal for prosthetic hand based on fuzzy logic technique: Bakalářská práce*. Brno: FEKT VUT v Brně, 2008. 40 s., 2 příl.

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V Brně dne 6. června 2008 ....

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Poděkování

Děkuji vedoucímu bakalářské práce Ing. Pawan Kumar Pathaka za účinnou metodickou, pedagogickou a odbornou pomoc a další cenné rady při zpracování mé bakalářské práce.

V Brně dne 6. června 2008 ....

podpis autora

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1. INTRODUCTION

A common approach in designing upper extremity prostheses is to follow this basic rule: the more distal the amputations, the more benefit a prosthetic fitting will be because there is a corresponding increase in automatic control. Prosthetic hands are the hands which hope to recapture their ability to perform complicated physical movements of the lost human hands. These hands would have almost the same dynamics as the neuromuscular control systems, mechanical properties of the muscles, and the stretch reflex of fingers as in a natural human hand. EMG is a suitable approach for human – machine interface in the prosthetic hand control.

The Electromyogram (EMG) is the signal measured by placing conductive elements or electrodes on the skin surface, or invasively within the muscle. Surface EMG, or skin EMG is used more often because its non-invasive character makes it safer and easier to use. The Electromyogram (EMG) is useful in the field of both medicine and engineering. The under section describes the relevant background knowledge on muscle architecture and how the muscle electricity is generated and detected. It provides many important and useful applications, but it has many limitations which must be understood, considered and eventually removed so that the discipline is more scientifically based and less reliant on the art of use. Electrode potentials associated with muscle activity constitute the Electromyogram, abbreviated EMG.

A pattern recognition system can be divided into feature extraction stage, feature selection stage and classification stage. First, the feature extraction is performed on the raw data to extract the features of the input patterns. Next, a smaller set of meaningful features that best represent the patterns are identified in the stage of feature selection. In the classification stage, a specific pattern is assigned to a specific class according to the relations that are established during the training or learning period.

Fuzzy Logic provides an approximate but effective means of describing behavior of systems that are too complex, ill-defined or not easily analyzed mathematically. Fuzzy variables are processed using a system called fuzzy logic controler. It involves fuzzyfication, fuzzy inference and defuzzyfication. The fuzzyfication process converts a crisp input value to a fuzzy value. The fuzzy inference is responsible for drawing colclusions from the knowledge base. The defuzzyfication process converts the fuzzy control actions into a crisp control action.

Within the frameworks of bachelor project, a study has been done of the basic characteristics of EMG (Electromyogram) signal for classification of differnt type of motions (ie. limited to open and close), by measuring and analysing the signal for multifunctional prosthetic hand. The signal recording was achieved in lab with the help of BIOPAC instruments. The recording and preanalysis were part of my previous work. The present work includes Classification and Analysis. Clasification was performed using Fuzzy Inference System (FIS) and Analysis was done with the help of MATLAB software (Fuzzy logic toolbox). I intend to design a decision maker which determines the motion performed based on the values input through the EMG system after fuzzyfication.

2. PROSTHETIC HAND

A common approach in designing upper extremity prostheses is to follow this basic rule: the more distal the amputations, the more benefit a prosthetic fitting will be because there is a corresponding increase in automatic control. Prosthetic hands are the hands which hope to recapture their ability to perform complicated physical movements of the lost human hands. These hands would have almost the same dynamics as the neuromuscular control systems, mechanical properties of the muscles, and the stretch reflex of fingers as in a natural human hand. EMG is a suitable approach for human – machine interface in the prosthetic hand control. After World War 2, with the huge increasing young amputees, the need for better limb control became more apparent. This led to technology being concentrated on developing a new knee that would stabilize, during weight bearing but swing freely during walking.

The design of body-powered upper-limb prostheses has experienced few major breakthroughs since early 1960´s. Upper-limb prostheses are controlled by body or external power and are either hook or hand-shaped. Persons with amputation frequently declare discontent with the actual state of upper-limb prosthesis technology, noting numerous shortcomings with their prostheses, such as functionality, reliability, ease of use, weight and energy consumption.

The 1970´s then saw the development of „Modular Assembly Prosthesis“ which allowed the assembly of prosthesis from a series of stock components. Then, in the 1980´s, with the development of materials in the aircraft industry, the world´s first carbon fiber prosthetic system was made. This technology promoted high strength and light weight system. Then in the 1990´s, development into the first commercially available microprocessor controlled prosthetic knee was carried out called the intelligent prosthesis (IP) . The unit is programmed to each individual user during walking to achieve the smoothest, energy saving pattern. It reacts to speed changes but its intelligence does not extend to understanding environmental considerations such as stairs, ramps or uneven terrain.

Nowadays hand amputees have the option of several kinds of prosthetic device. Except cosmetic hands or mechanically activated grippers there are a number of electrically driven hands available. Many of these are activated by the user contracting a single muscle – final electromyographic signal activating the opening or closing of a single degree of freedom device. The speed and strength of the grip may be proportional with the read signal. The expected use for the artificial hand is as a robotic anthropomorphic device with multiple degrees of freedom. For the control of these more complex hands a more advanced human-machine interface is needed, including multiple EMG electrodes and a suitable pattern recognition system to interpret the raw signal. Ideally this system would require the user to undergo minimal training and hence the control inputs should be as natural as possible. Until muscles intrinsic to the hand are responsible for the fine grip and movement, muscles in the forearm are responsible for the coarse grasp shape made by a human hand. After a hand amputation many remaining muscles in the forearm can still be used by the amputee. Read EMG signals from these muscles can be used as the control surface for the prosthetic device.

The system can also be used by able-bodied individuals as a machine interface to replace traditional controllers such as joysticks. The benefits of this include less fatigue and a more natural movement. A successful controller will need minimal training of the operator.

Researchers have used various methods – such as multilayer neural network, Hidden Markov Models and Fuzzy ARTMAP Networks – for identifying limb motion based on EMG signals. Control of an artificial hand, either a robot manipulator or a prosthetic device, is achieved by placement of a number of EMG electrodes at specific locations on the skin surface of the forearm. Each sensor measures the surface potential at two points. The potential difference is directly proportional to the amount of contraction of the underlying muscle [1].

3. ELECTROMYOGRAM (EMG)

The Electromyogram (EMG) is the signal measured by placing conductive elements or electrodes on the skin surface, or invasively within the muscle. Electromyogram is made of Electro - which means the electric signals, Myo - which means the Muscles, and of course gram - which means a recording with a device.

Surface EMG, or skin EMG is used more often because its non-invasive character makes it safer and easier to use. The Electromyogram (EMG) is useful in the field of both medicine and engineering. The under section describes the relevant background knowledge on muscle architecture and how the muscle electricity is generated and detected. It provides many important and useful applications, but it has many limitations which must be understood, considered and eventually removed so that the discipline is more scientifically based and less reliant on the art of use. Electrode potentials associated with muscle activity constitute the Electromyogram, abbreviated EMG. These potential may be measured at the surface of the body near a muscle of interest or directly from the muscle by penetrating the skin with needle electrodes. Since most EMG measurements are intended to obtain an indication of the amount of activity of a given muscle, or group of muscles, rather than of an individual, action potential from the fibers constituting the muscle or muscles are measured. As with EMG Electrodes, they pick up potentials from all the muscles with in range of electrodes. This means that potentials from nearby large muscles may interface with attempts to measure the EMG from smaller muscle.

3.1 Electrical activity of active muscle – action potential (AP)

AP rises if depolarizating flow step over the potential on level door-step and evokes opening the channel Na^+, wich faces to increasing ‘positivism‘ inside cell and to gradual development AP. If muscle is freely enabled, action potential rising in motoric cortex is spreading in brain pyramidal way to cells fore corners spinal, where is hand down to motoneurons. From motoneurons AP is led by all his branchs to single muscular grains and further it spreads over their membranes.

Fever, going over motoric nerves, notching various motoric units in any other moment, so that didn´t contract at the same time, but in turns – asynchronous. Their contraction however upon yourself tie together. Contraction of each of muscular grains appropriate definite excited MU is action one – shot. Every nervous shock evokes after lapse of latent time only one contraction wave, running after fibre from innervation seats behind wave emotional (with definite shift phase). Speed of emotional and contraction waves may be at single grains considerably different. Rise of contraction wave grains is signalling AP.

In surface EMG goes through AP over contiguous muscular tissues, mainly oil and leather, on its surface are detected. EMG signal is outcome succession of motor unit action potentials, that are detected with surface electrode in proximity of contracted muscular grains.

Electric activity of muscle is exploit for judge mechanical activities possibility relative association of registered electric signals with quantities, that describes the mechanical effect contraction. Possibility of assignment in some enough certain cases can lead along till compensation. Generally is but assignment of electric activities (EA) to values mechanical make difficult for row influences. Their omission can conduct at interpretation of results to out of focus and simplified opinion on real conditions. Source of next distortion can be proper registration progress, used device and the way of EMG quantification, especially gained just by the help of dermatic electrodes.

3.2 Characteristic of EMG signal

Electromyographic (EMG) is investigative method, based on surface scan or scan of intramuscular muscular activities. It records the change of electric potential at muscular activities. EMG provides considerable possibilities of use, but at the same time has a lot of limitation. It is necessary, for the limitation to be fully understandable, well-judged and possibly displaced, so that a method can be alleged on scientific base, and not only on simple using. EMG is too easy on utilization, but also too easy for misuse.

EMG signals are the electrical manifestation of neuromuscular activity associated with contracting muscles. It is well established that the amplitude of the EMG signal is stochastic (random) in nature and can be reasonably represented by a Gaussian distribution function. The amplitude of the signal can range from 0 to 10 mV (peak-to-peak) or 0 to 1.5 mV (rms). The usable energy of the signal is limited to a 0 to 500 Hz frequency range, with the dominant energy being in the 50-150 Hz region. Usable signals are those with energy above the electrical noise level [9]. An example of the frequency spectrum of the EMG signal is presented in Figure 3.1.

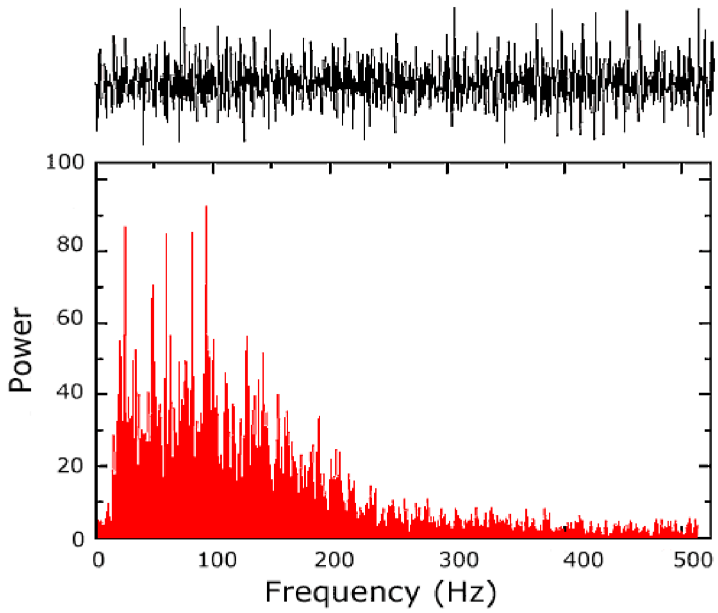


Fig. 3.1 Frequency spectrum of the EMG signal

3.3 Acquisition of EMG

As the brain´s signal for contraction increases, it both recruits more motor units and increases the „firing frequency“ of those units already recruited [2]. All muscle cells within one motor unit become active at the same time. By varying the number of motor units that are active, the body can control the force of the muscle contraction. When individual motor contract, they repetitively emit a short burst of electrical activity known as the motor unit action potential (MUAP) [3]. It is detected by electrodes on the surface of the skin in proximity of the motor.

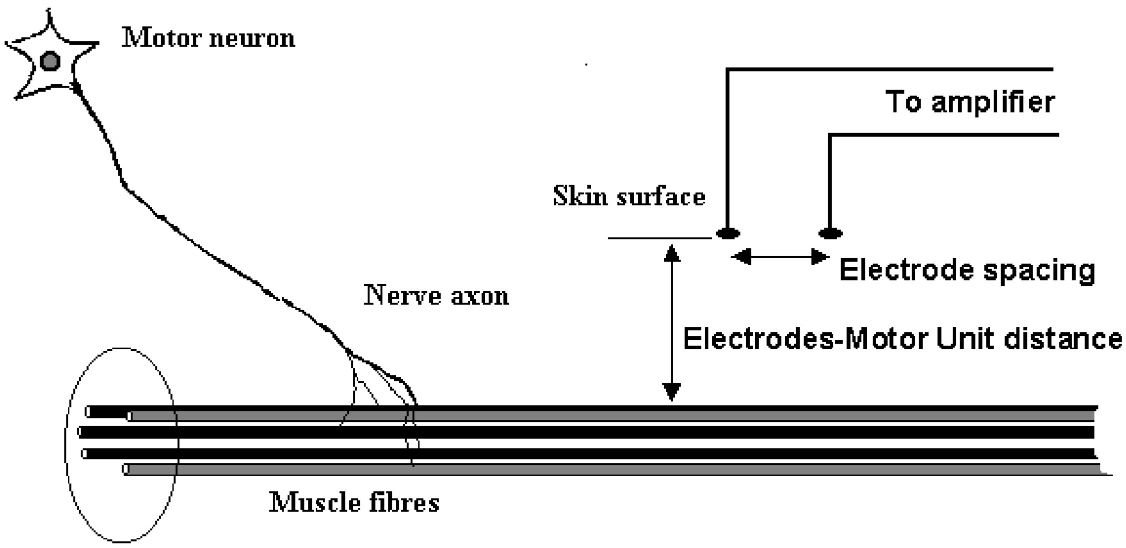


Fig. 3.2 MUAP detection

The MUAP is the electrical response to the impulse from the axon. (Fig. 3.2)

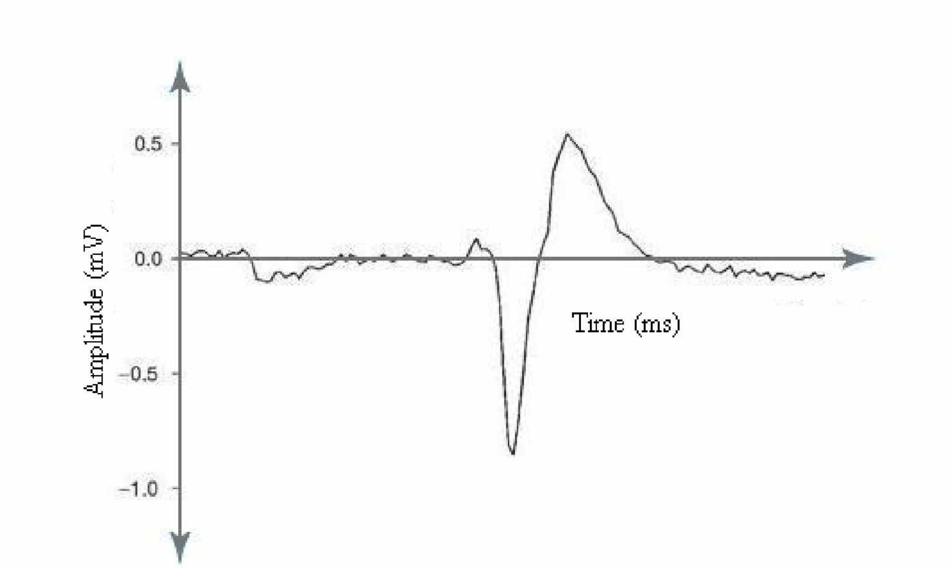


Fig. 3.3 Action potential (AP) of one motor unit

The contraction of a muscle recruits a number of motors during a period of time. When several motor units are active, a random interference pattern of electrical activity results detection of EMG signal [3]. The usable energy of the signal is limited to the 0 to 500 Hz frequency range. Usable signals are those with energy above the electrical noise level [4]. There are many factors that influence the EMG signal´s detection. These include the electrode structure and its placement on the surface of the skin above the muscle.

3.4 EMG electrodes

Muscle contraction is created by twitching of muscle fibres, the level of contraction being determined by both the number of fibres activated and the rate at which they twitch. The collection of muscle fibres, activated by a single neuron is called a single motor unit. The electrical potential of individual motor units can be measured with fine wire or needle electrodes to determine the level of activity. While these electrodes are widely used in clinical applications, they are unsuitable for the practical applications under consideration. The EMG signal as measured at the skin surface is the spatial and temporal sum of individual motor units within multiple muscles in the vicinity of the recording electrode. The signal is stochastic with a typical amplitude of 0-6 mV. The usable frequency range is 0-500 Hz with most energy concentrated from 50-150 Hz. Ambient electrical noise is a serious problem because the human body is an excellent antenna and the amplitudes of this noise - particularly in the 50Hz range - are far greater than the EMG signal. Unfortunately this spectrum of the EMG signal is exactly the area where the most information is located. The best results were obtained by using instrument amplifiers with a high CMRR (120dB) and feeding the inverted common-mode signal from each electrode pair back onto the arm (Fig. 3.4). This very effectively cancels out all unwanted electrical signals, accordingly there has been no need to carry out any 50 Hz filtering after gatherint the singal [1].

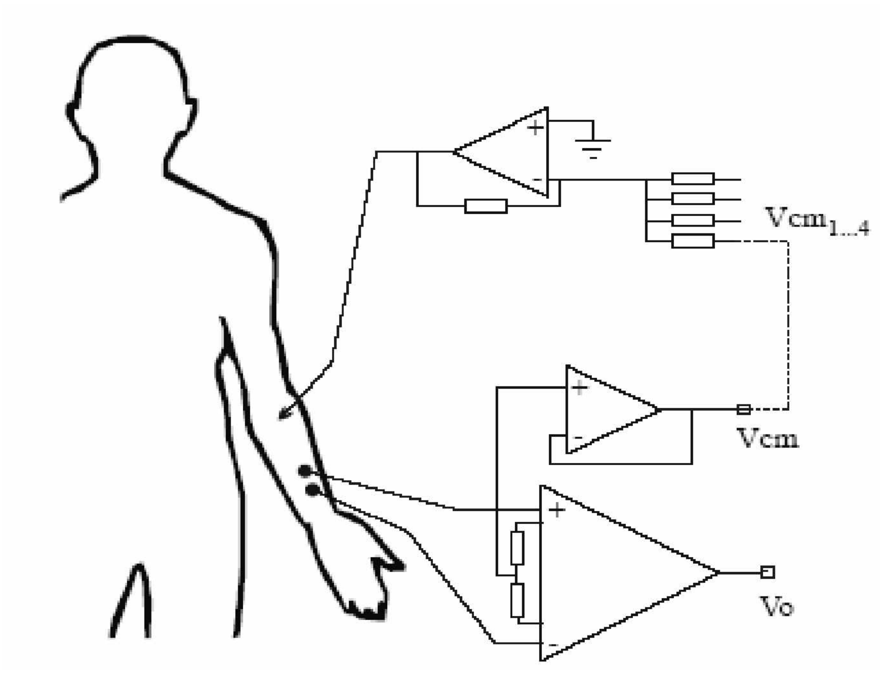


Fig. 3.4 EMG insturmentation showing electrode pair and feedback of common-mode signal to arm

Electrodes needed to be applied in pairs at specific locations on the skin surface. Placing the electrodes at the correct spot is significant, because even small differences in location can lead to large changes in the resulting signal. For positioning the disposable electrodes an electrolytic gel needed to be used with the Ag/AgCl discs to establish electrical contact with the skin tissue. This led to the electrodes slipping on the now wet skin surface. This caused motion artefacts in the signal, these appeared as large voltage spikes whenever one of the disposable discs moved. The other major problem with this system was that amplification of the signal was performed some distance from the actual electrode surface. This meant that electrical noise induced in the connecting cabling could significantly degrade the signal, because the EMG signal has such a low amplitude [1].

3.4.1 Active electrodes – electrodes with built-in amplifier

To counter many of these problems an active electrode system was developed. To amend the signal-noise ratio it was proposed to have amplification occurring as close as possible to the electrodes themselves. A fixed geometry of the electrode surfaces would assist in relocating the electrodes at the correct location. If the electrodes could be applied dry (without any conductive gel) this would aid in the application phase as well as reducing the likehood of motion artefacts appearing in the signal [1].

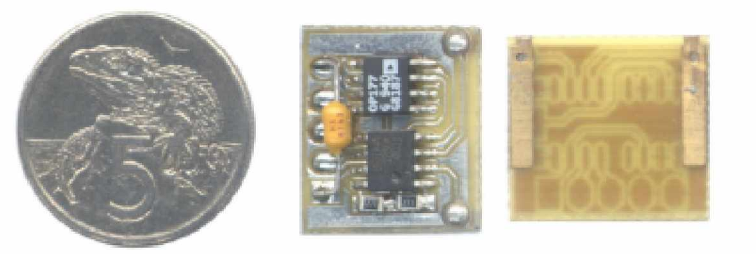


Fig. 3.5 Active electrode

The electrode detection areas consist of two gold plated rectangular surfaces on the bottom of a small board including the amplification circuitry. These each measure 10 mm x 2 mm and are spaced 12 mm apart. These bars are placed on the skin surface parallel to the direction of the muscle fibres. As illustrated in Fig. 3.4, each surface is connected to an instrumentation amplifier and the output voltage (V_0) is sampled by the computer. The common mode voltage (V_{cm}) of all electrodes is fed into a summing amplifier and the resulting inverted signal is then fed back onto the arm. Usually an Ag/AgCl electrode is used as the connection for this. It is placed at a point on the skin with minimal underlying muscle, typically in the elbow region [1].

3.4.2 Passive electrodes – electrodes without built-in amplifier

Passive electrodes require very good electrical contact with the skin surface, that is why a careful preparation of the skin is needed. Leather must be scrubbed on the skin, which further needs to be precisely cleaned with alcohol, to get off each of the oils. Contact Gel is also required to be used. Electrode should not touch the skin directly, but instead, there should be a thin ply of contact gel between skin and electrodes. That is why most electrode discs have a small hole in them. After the electrode is fixed into the skin, contact gel is injected by using a squirt.

Fig. 3.6 Passive electrode

3.4.3 Type of construction

1. **Surface electrodes** are used in measurement, in lead nerve, reflexologic and kineziologic studies. Usually they are smaller metal discs, wich fixate on ungreased skin with sticking - plaster. They are not suitable for investigation of action potentials of single motor units, because they entrap potentials from the digger surface, which records activity from more motoric units. Input resistence at fixation should be as small as possible.

2. **Needle electrodes** are used as in native elektromyography, such as studies of lead peripheral nerves. There have been various types : concentric, bipolar, homopolar.

3.4.4 Purpose of use

1. **Registration electrodes** can be needle and also surface. Active electrodes scan electric activity and are placed above belly surveyed muscle. Reference electrode is placed above sinew. Final EMG signal is voltage difference between the active and referential electrodes.

2. **Stimulative electrodes** are specially customised for stimulation call.

3. **Earthed electrodes** are surface electrodes, usually to form fixed belt electrodes.

Surface pan electrodes or self-gluing electrodes, mainly with Ag/AgCl surface, are required to be cleaned well mechanically and wash with petrol-alcohol. Needle electrodes sterilize themselves.

3.5 Feature extraction

The quantity of gathered data makes it cumbersome to work directly with raw EMG signal at the pattern recognition phase. The strategy is to reduce this information down to a smaller set of identifying characteristics by means of various feature extraction algorithms [1]. Feature extraction is a process by which signal attributes are computed and collected into a compact vector format. Feature extraction can be considered as data compression that removes irrelevant information and preserves relevant information from the raw data. The information extracted is still enough to describe the signal, but with a smaller set of data.

Each channel of the raw EMG signal is a discrete time series y(k). Many methods have been tried to characterize this time series for pattern recognition [1].

3.6 Grasp recognition

For the control of a robot hand we aim to identify the basic grasp shape being made by the user. In order to grasp and manipulate an object the human hand will first form a basic shape suitable for gripping the required item. This phase is known as preshaping. Once the style of grip being enacted is known the robot hand is commanded to move the fingers to the correct orientation. Recognizing this initial shape is the first task, completing the grasp can then be accomplished using feedback sensors within the fingers [1].

There are several basic grasp shapes that the human hand can form. Basic set of grasps consist of the following forms: large and small cylindrical, large and small spherical, pinch and key as illustrated in Figure 3.7.

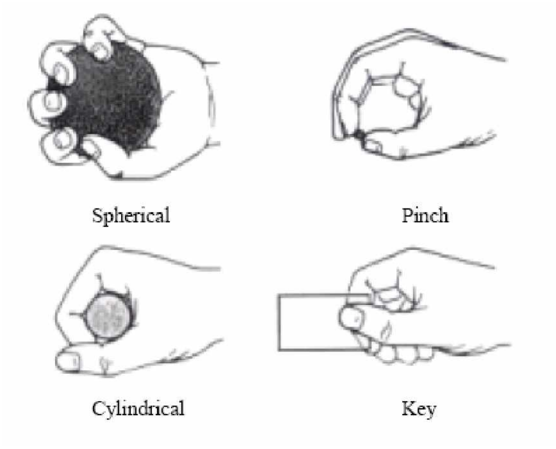


Fig. 3.7 Basic grasp shapes

Frequency domain
Signal in the frequency domain contains useful information which can be used to identify the signal. By the help of the Short-Tiem Fourier Transform (STFT), the incoming signal breaks into small blocks and performs an FFT on each segment. This shows, at which point in time the various frequencies are occuring. Between frequency and time resolution is a trade-off. Smaller data segments must be used to increase time resolution. Many different segment sizes and overlapping time windows were trialled with this technique. The resulting data set is still quite large, but does give greater recognition rates than a filtered time series [1].

Parametric modelling
The EMG signal´s power spectrum can be described as a pole-zero model. An autoregressive (AR), or all-pole model was used to model the time series as:

$$y(k) = -\sum_{i=1}^{P} a_i y(k-i) + e(k) \tag{3.1}$$

where a_i are the AR coefficients, P is the order of the model and e(k) an error term [1].

Wavelet decomposition
The Discrete Wavelet Transform (DWT) is a fast, linear operation. It is similar to the FFT in that can be viewed as a rotation in fiction space - the time domain changes into a different domain. While with the FFT, the new domain has basis functions of sines and cosines, the DFT bases are more complicated and known as wavelets. There are many different families of wavelets and several of these were examined [1].

4. BIOPAC STUDENT LAB

The Biopac Sudent Lab (BSL) was designed to be a useful tool in helping students learn some basic physiological concepts. This is much more than a simulation program, or concepts and pictures presented in a textbook. This data is like an X-ray that lets you look inside your body to see its inner workings [5]

One way how the BSL works is like a video camera connected through a VCR into a television set.

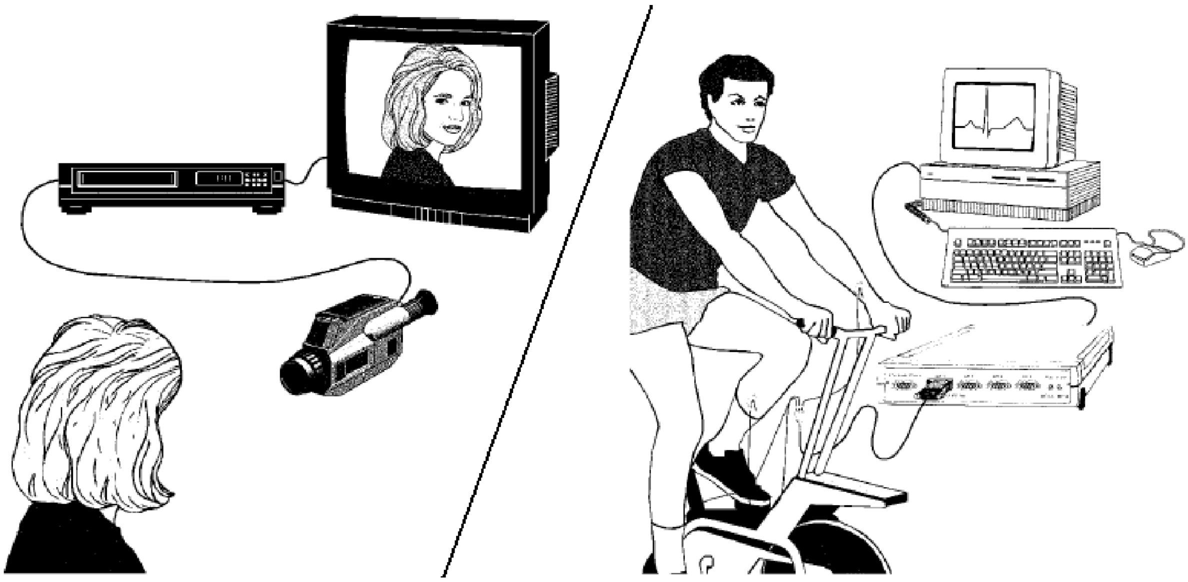


Fig. 4.1 The way of Biopac Student Lab function

Whereas cameras record visual information, the BSL records information about your physiological state, whether in the form of your skin temperature, the signal from a beating heart or the flexing of an arm muscle [6]. These signals are transferred between you and the BSL by a cable. The type of physiological signals you are measuring will determine the type of device on the end of the cable. When the signal reaches the BSL, it is converted into a format that allows the data to be read by a computer. The signal can be displayed on the computer screen, much like the video images from the camera are displayed on the television set. It takes about 1/1000 second from the time, a signal is picked-up by a sensor until it appears on the computer screen. The computer´s internal memory can sack these signals much like the VCR and can save the video images. And like a video, you can edit and manipulate the information stored in a BSL computer file [5].

4.1 BSL system components

The BSL is a complete system that consists of software and hardware components.

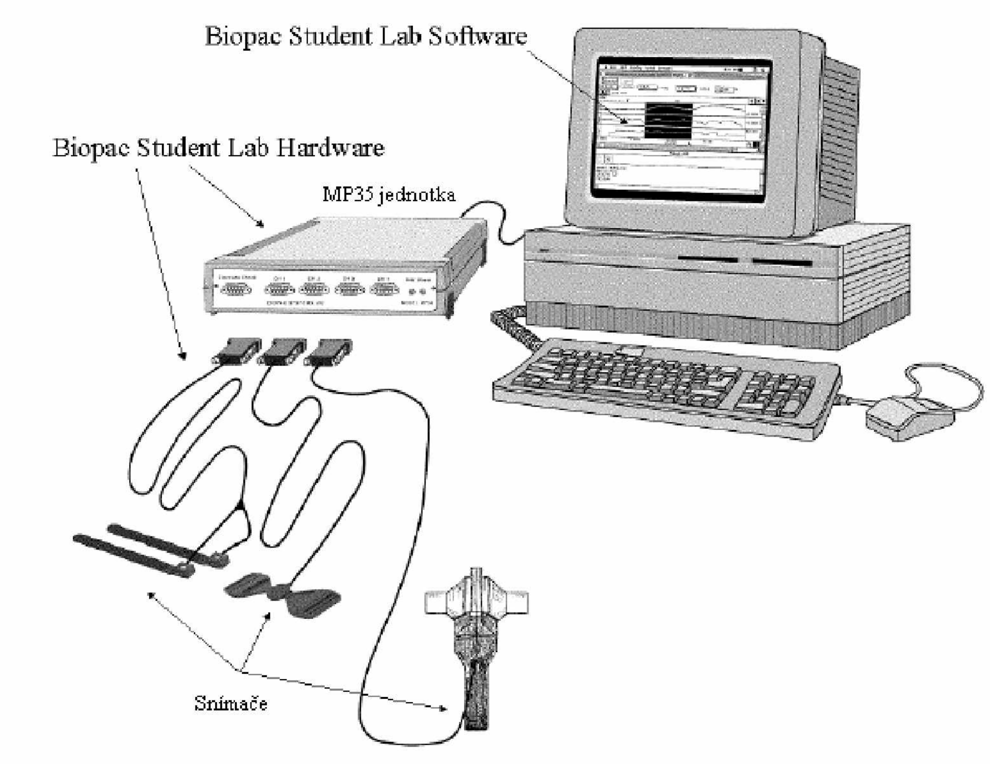


Fig. 4.2 Software and hardware parts of BSL

4.1.1 Software

A Software here is the BSL program that runs on the computer. The software reads in the numbers representing the electrical signals coming into the MP35 acquisition unit and displays them as a waveform on the computer screen (in our analogy, the computer acts like the VCR and the monitor like the TV set). The software guides the user through the lesson with buttons and text and alson manages data saving and data review. [5]

4.1.2 Hardware

Hardware includes the MP35 acquisition unit, connection cables, wall transformer, transducers, electrode cables, electrodes, headphones and other accessories. The electrical signals from transducers and electrodes are very minute, with amplitudes sometimes in the microvolt range. The MP35 unit amplifies these signals, filters out unwanted electrical noise or interfering signals, and converts these signals to a set of numbers that the computer can read. These numbers are sent to the computer via a cable. [5]

5. SIGNAL RECORDING AND PREPROCESSING

5.1 Muscles

Each electrode is placed above a specific muscle in the forearm. The system can handle up to eight electrodes at the same time. Typical is the use of four electrodes placed on extensor muscles of the upper forearm. These muscles can be separated into three parts: Extensor Pollicis Longus and Extensor Pollicis Brevis are responsible for thumb movement, Extensor Communis Digitorum is related to index and middle finger motion while Extensor Carpi Ulnaris indicates little finger activity. This selection is suitable for able-boiled subjects but amputees will not necessarily have all these muscles inviolate [1].

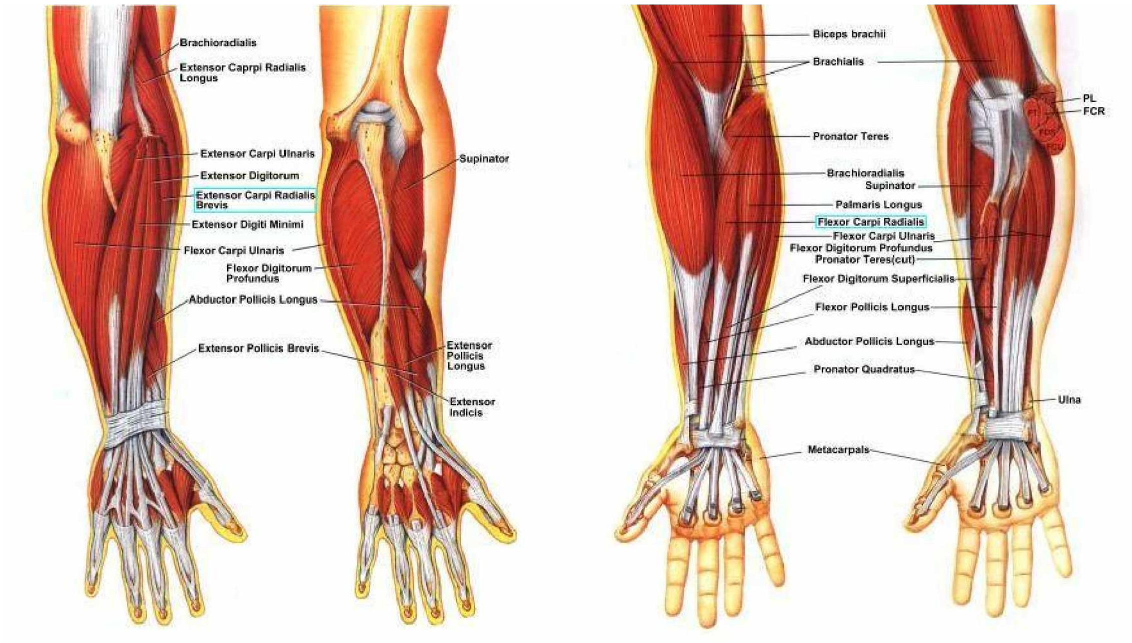


Fig. 5.1 Forearm muscles

5.2 Signal Measurement

The needed measurements for the processing were done in two visits to the lab E234 in Department of Biomedical Engineering. For recording I have used:

- A Computer for storing and implementing the Biopac unit with the data sets provided for processing.

- Biopac M35 unit acquired data from the muscles and collected it to form a data set for further processing after forming intelligent data sets.

- Software BSL Lessons 3.7, was a software running on the computer to classify and display the actual results and data values.

- Cable to connect the muscle with the Biopac M35 unit for data transfer.

- Passive electrodes with contact gel (from firm Schiller).

- Handbook with the process of measuring for reference .

- Two 'donors' – Balázs Lábsky(Subject 1) and György Szajkó(Subject 2)

The suitable muscle group was achieved after rigorous processing and testing on different muscles to finally yield the following muscles Flexor Carpi Radialis, Extensor Carpi Radialis Brevis and those of the foreleg, which eventually form the basis of my study. All other muscle sets did not give the intended results when data from these sets was recorded for processing.

Two needful electrodes were placed on skin surface, on muscles Flexor Carpi Radialis, Extensor Carpi Radialis Brevis and the third , the earthed electrode, was put on the foreleg.

Measuring process: subjects have to perform two basic movements with their wrist – opening and closing. Before every measurement, calibration of the device was required by the given process. I recorded 200 signals from both subjects, namely, 100 close and 100 open.

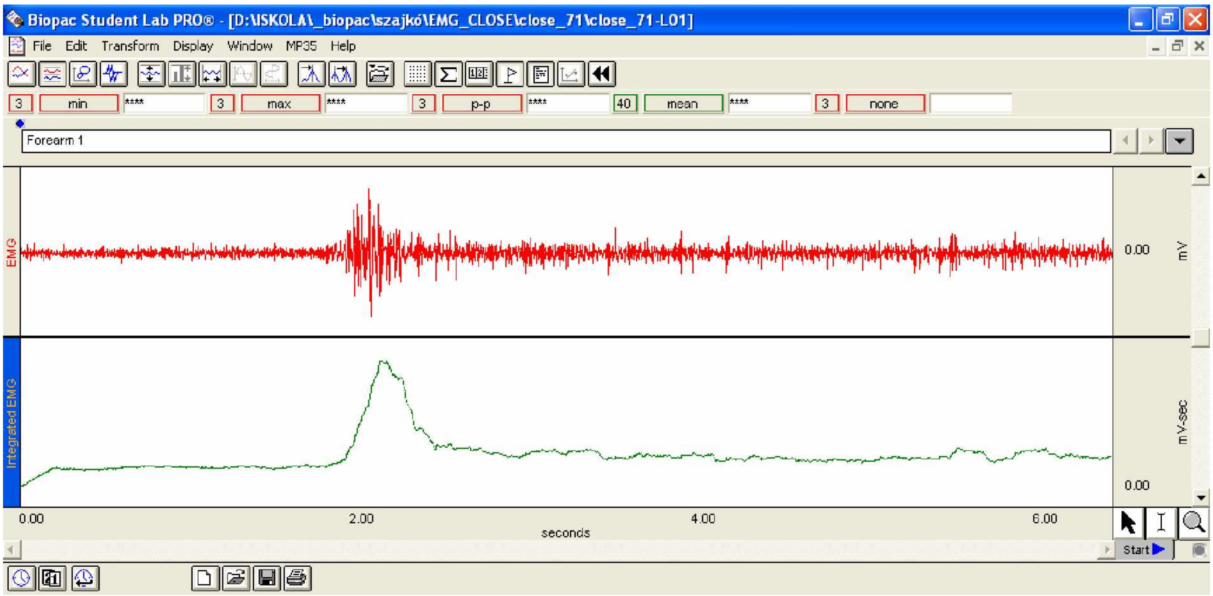


Fig. 5.2 Sample of an EMG signal (close)

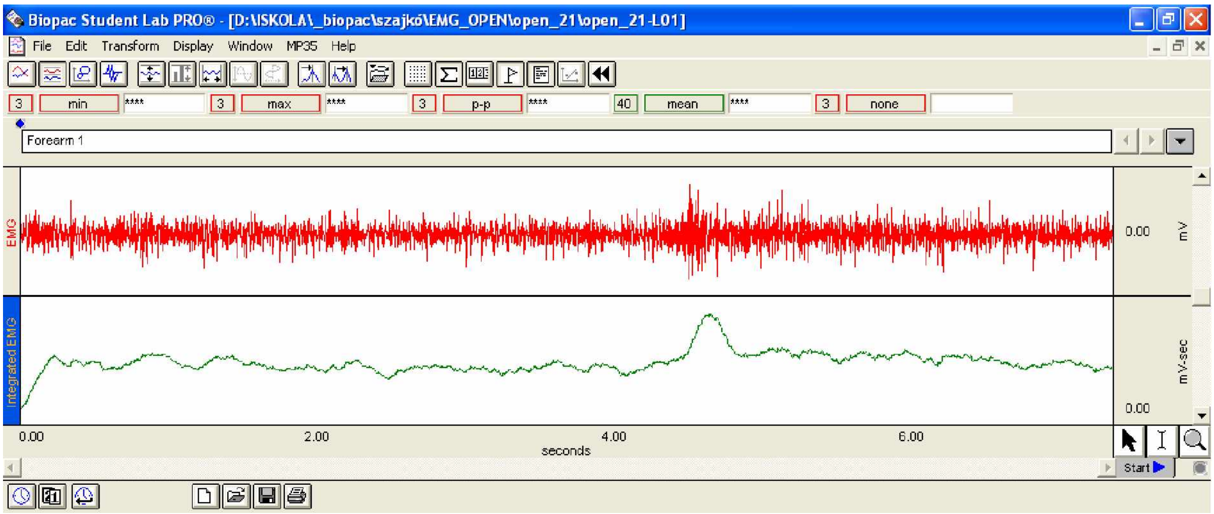


Fig. 5.3 Sample of an EMG signal (open)

5.3 Flow diagram for EMG data translating to usable format for Matlab

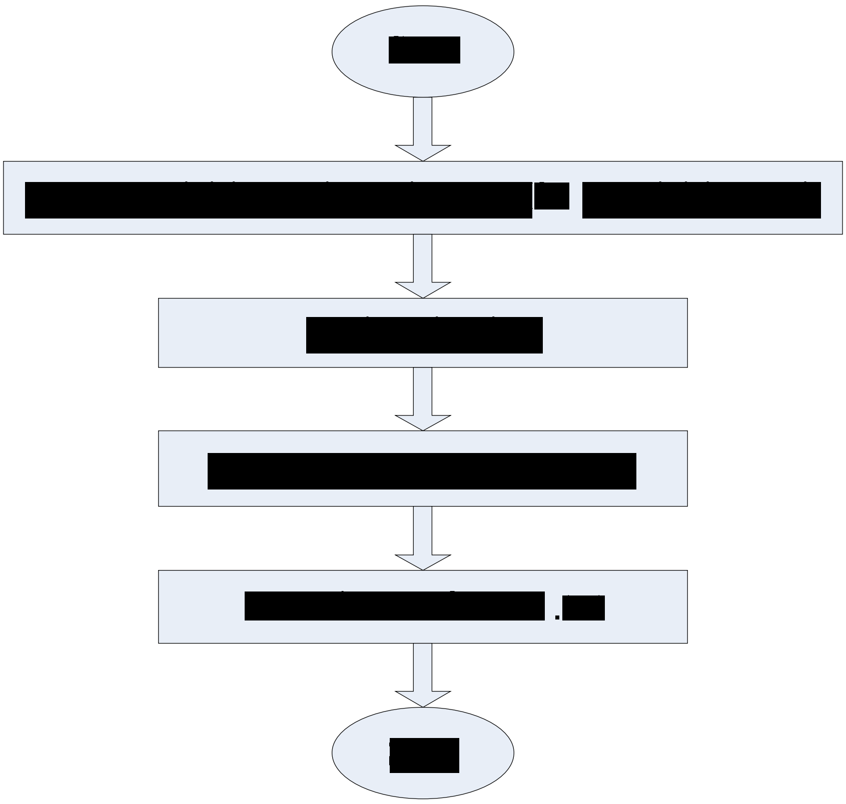


Fig. 5.4 EMG data translation to usable format for Matlab

5.3.1 Flow diagram for EMG threshold

Because each signal is different, the starting points can be placed a little bit different, every time (which depends on the start of the grasp). It is therefore evident from the data available to us on processing that there is no concrete point for starting. As a result the calculation of Threshold was performed in Microsoft Excel to have error free results and efficient implementation. The method was the following:

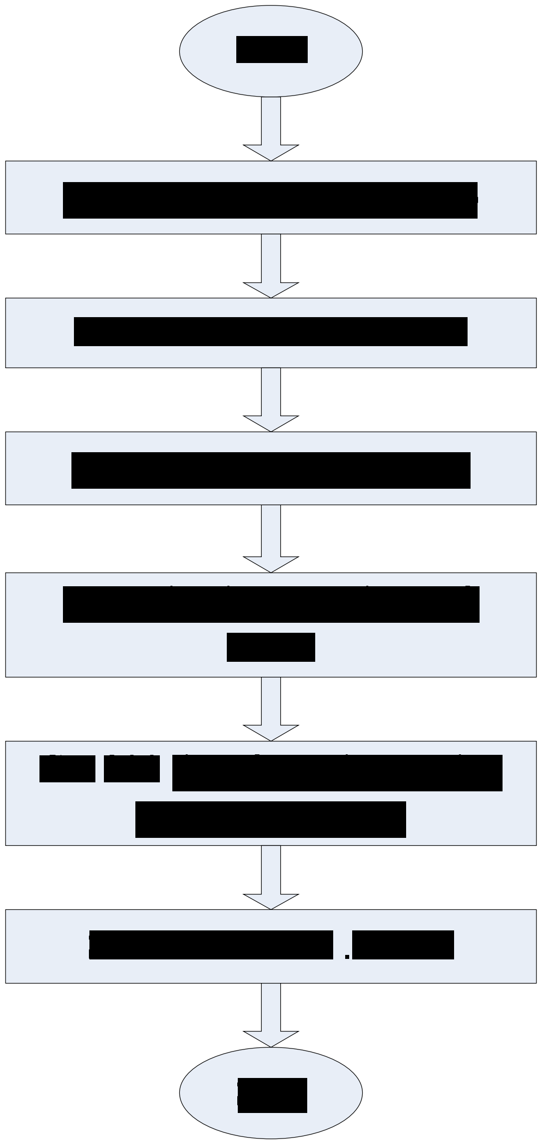
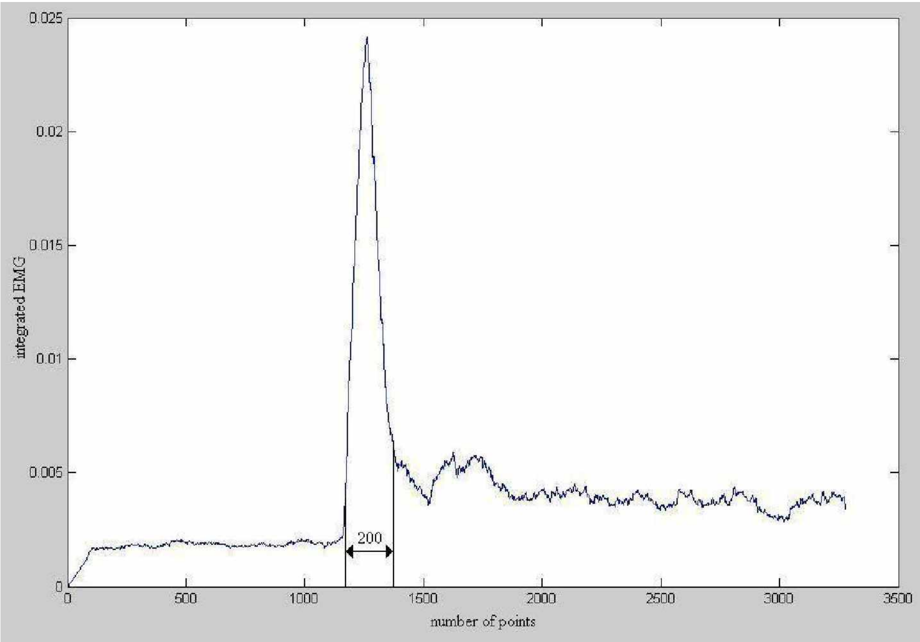


Fig. 5.5 EMG threshold

5.4 Data preprocessing

The measured Biopac platform based data was changed to the readable format for Matlab – Every time, the data was opened, then saved to .txt file, which was usable for the system. Four data files were created: 'Labsky_close', 'Labsky_open', 'Szajko_close', 'Szajko_open'. Each data file contained 100 data values, each data consisting of approximately 3 - 4000 points. The next part of my work was to select 200 points from the usable data range, which is similar to 400 ms. An example method is shown below:



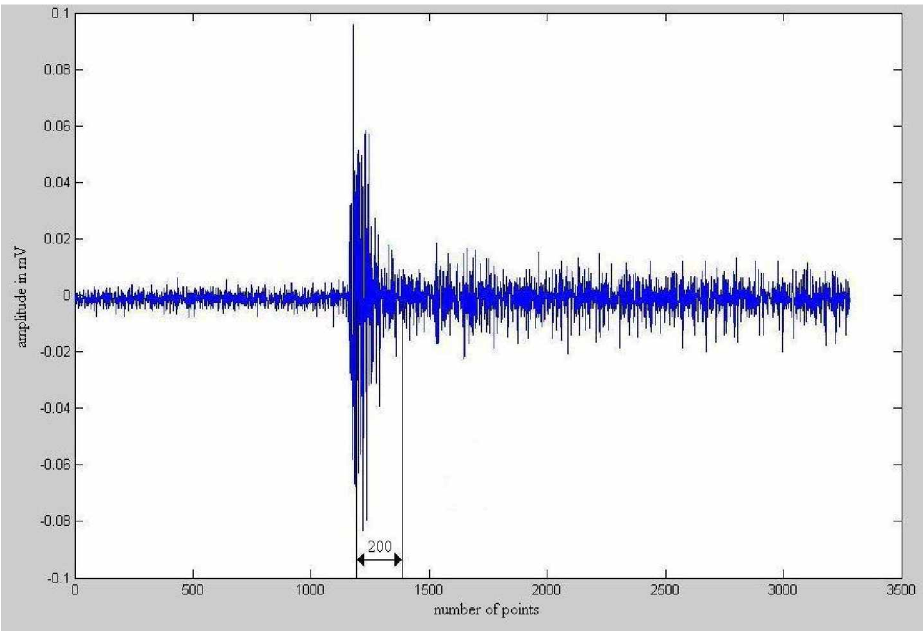


Fig. 5.6 The threshold method (for close motion)

In this example, the starting point was established at 1180. Then the .txt file was copied to Microsoft Excel, and 200 points were then cut from the data (between 1180 to 1379). From these data the main matrix was made.

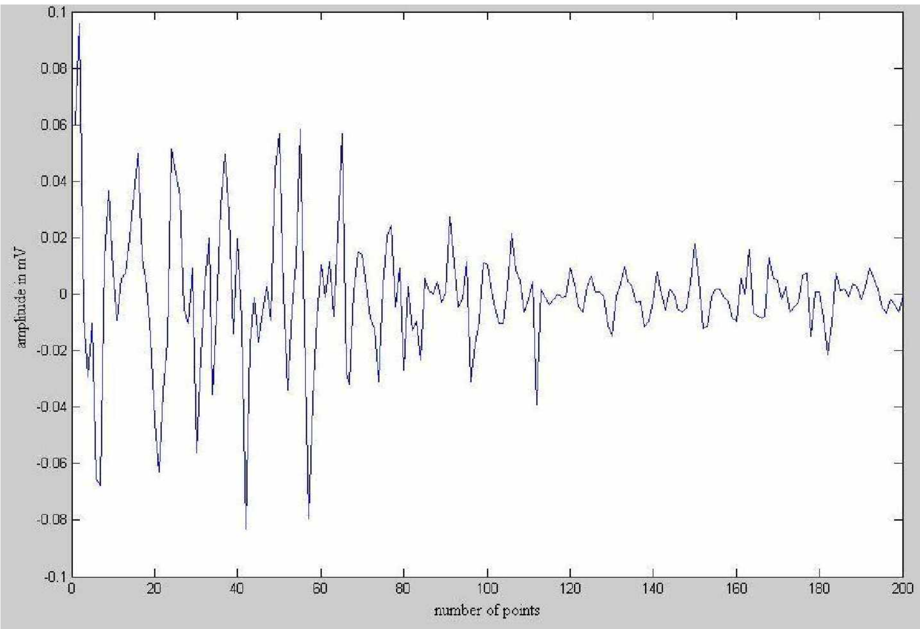


Fig. 5.7 The selected sample (close motion)

6. PATTERN RECOGNITION

A pattern recognition system can be divided into feature extraction stage, feature selection stage and classification stage. First, the feature extraction is performed on the raw data to extract the features of the input patterns. Next, a smaller set of meaningful features that best represent the patterns are identified in the stage of feature selection. In the classification stage, a specific pattern is assigned to a specific class according to the relations that are established during the training or learning period [7].

The success of a pattern recognition system depends almost entirely on the choice of features representing the data sequence. The EMG signal can be represented in various forms or parameters. Different forms or parameters result in different analytical complexity and functional advantages. The algorithms for EMG feature extraction or parametric representations are described below [7].

6.1 Traditional parametric features

The traditional parametric features of EMG signals include Integrated EMG, Variance, Zero-crossings, Slope-sign changes and Waveform length. They are all from real-world processes. However, calculation complexity is the major concern. All of them can be calculated in real-time. For each feature, N is the window length for computing the features and X_k denotes the *k*th sampling data in the window [7].

6.1.1 Integrated EMG (IEMG)

This parameter is found by calculating the summation of the absolute values of EMG sinals. It can be treated as a signal power estimator [7]. It is defined as

$$IEMG = \sum_{k=1}^{N} |x_k| \tag{6.1}$$

6.1.2 Variance

This parameter is used to estimate the power of the EMG signal [7]. Its definition is given by

$$v_{ar} = \frac{1}{N-1} \sum_{k=1}^{N} {x_k}^2 \tag{6.2}$$

6.1.3 Zero-crossing (ZC)

Zero-crossings is basically the count of the number of times the waveform crosses the zero axis. This parameter is used to get the rough property in frequency domain [7]. It is calculated as:

$$\begin{gathered} ZC = \sum_{k=1}^{N} \operatorname{sgn}((x_k - 0.4) * (x_{k-1} - 0.4)); \\ \operatorname{sgn}(x) = \begin{cases} 1, \text{ if } \ x > 0 \\ 0, \text{ otherwise} \end{cases} \end{gathered} \tag{6.3}$$

6.1.4 Slope-sign change (SSC)

This is another parameter to represent the frequency information. As mentioned above, a suitable value shall also be included to reject the disturbance effect [7]. The criterion for the parameter selection is defined by the consecutive samples as:

$$[X(k) - X(k-1)] * [X(k) - X(k+1)] \geq 0{,}003 \tag{6.4}$$

If the connection is satisfied, the slope-sign change value is increased.

6.1.5 Waveform length (WL)

A featutre which provides information on the waveform complexity in each segment is the waveform length [7]. This is simply the cumulative length of the waveform over the time segment defined as:

$$\text{wavaform length} \approx \sum_{k=1}^{N} |x_k - x_{k-1}| \tag{6.5}$$

6.2 Flow diagram for traditional parametric features calculation in Matlab

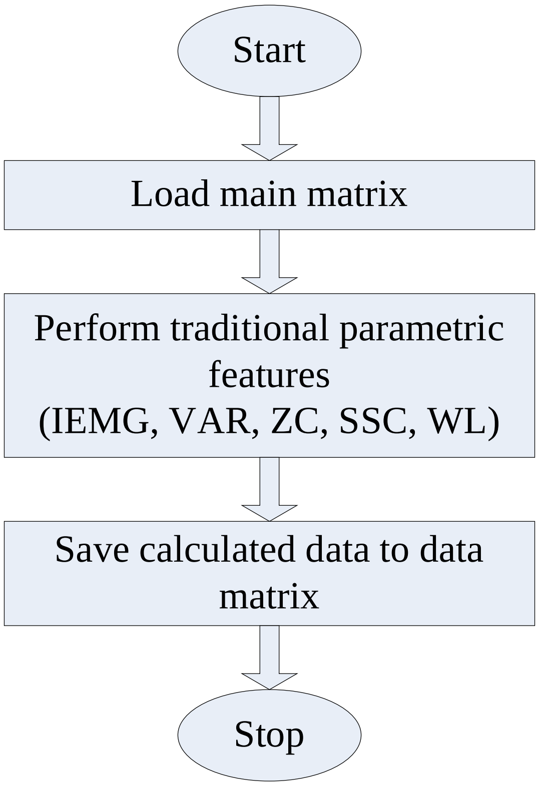


Fig. 6.1 Feature calculation in Matlab

6.3 Classification

Cutting of the recorded data has been done based on the threshold, mentioned earlier. Data were saved to 'matrix_main'. Next step was to study and allocate, which motion was performed with the wrist – with the help of traditional parametric features. The recorded data are plotted and analyzed for features: Integrated EMG (IEMG), Variance (VAR), Zero-crossing (ZC), Slope-sign change (SSC) and Waveform length (WL).

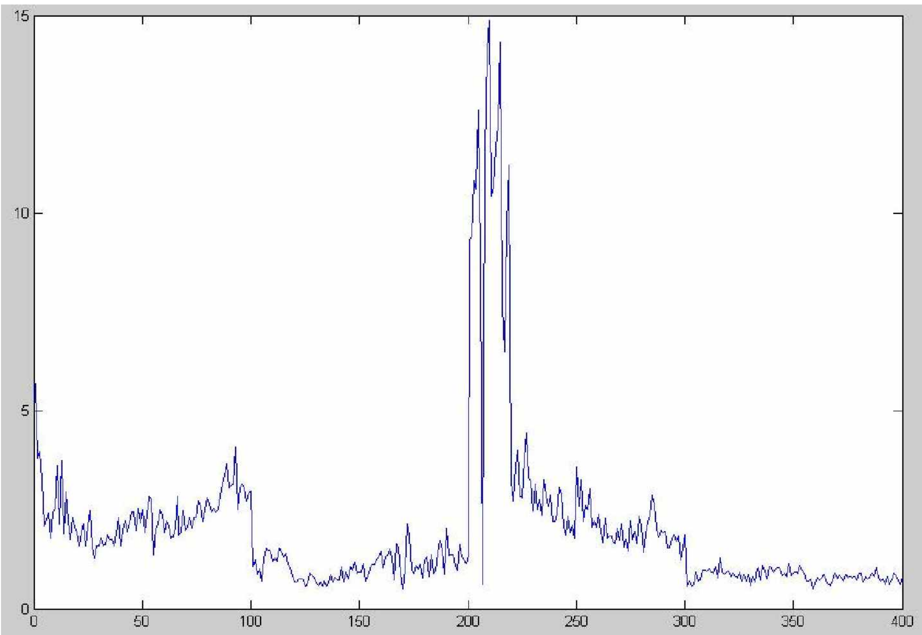


Fig. 6.2 Variation of IEMG

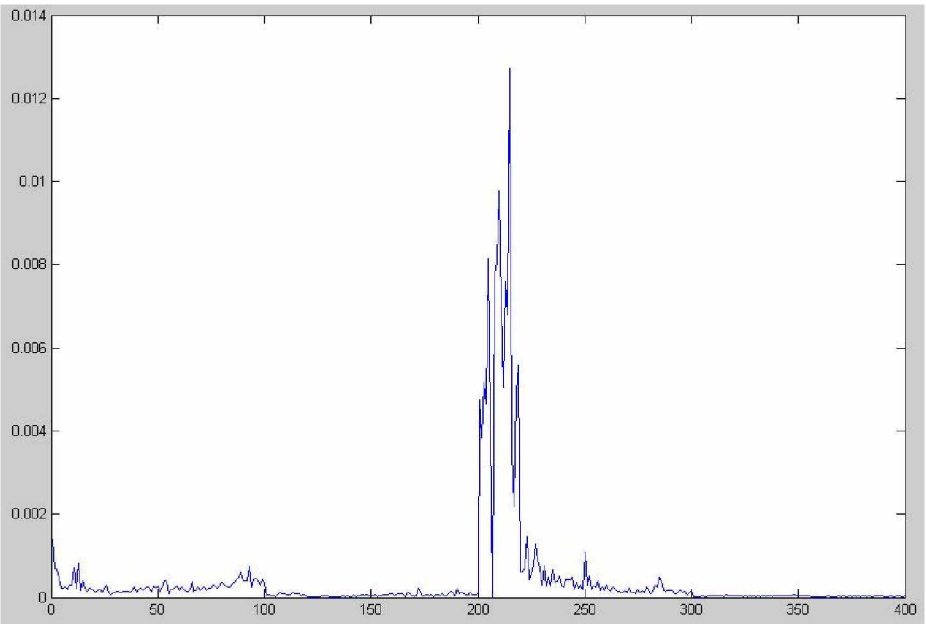


Fig. 6.3 Variation of VAR

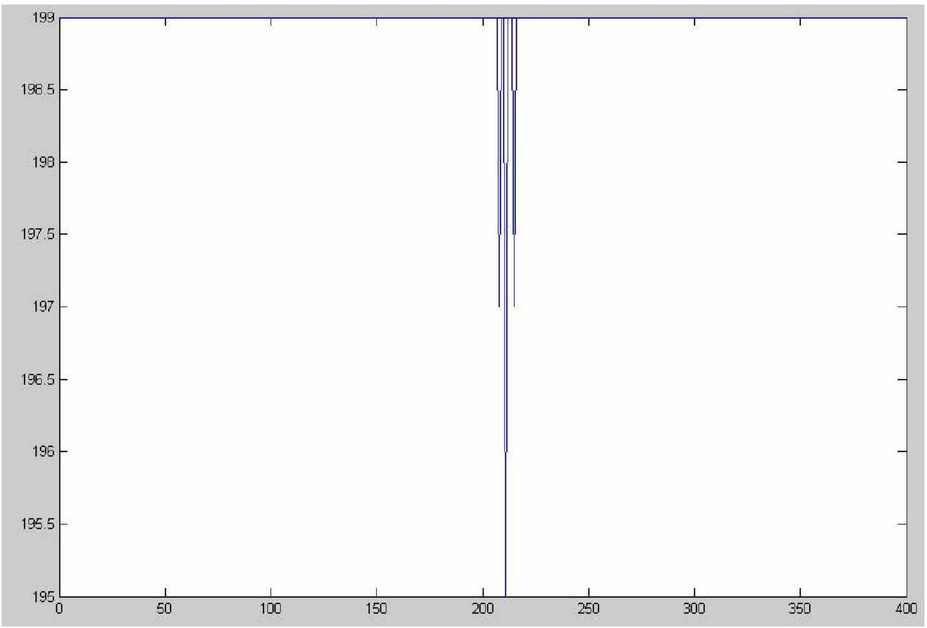


Fig. 6.4 Variation of ZC

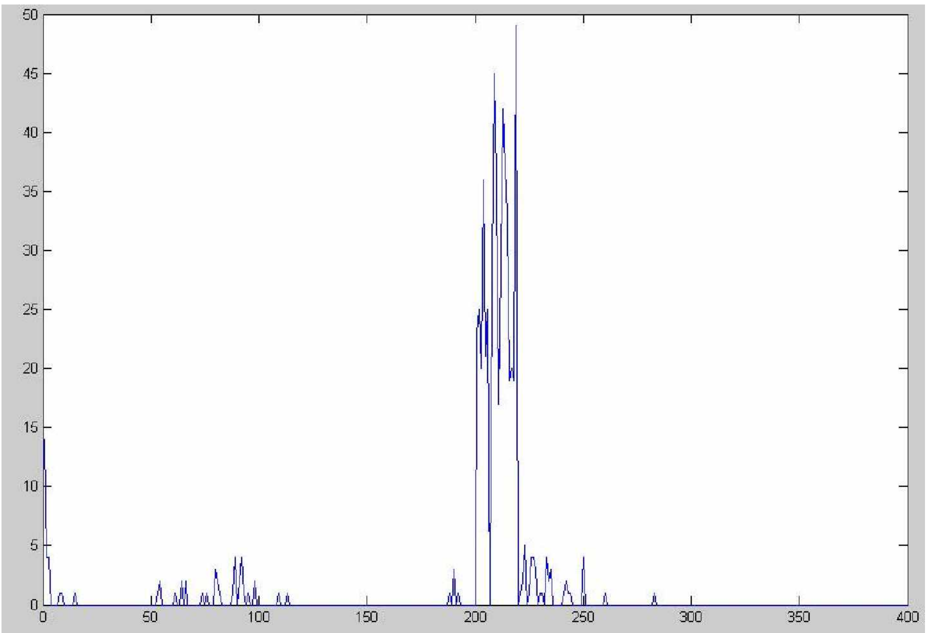


Fig. 6.5 Variation of SSC

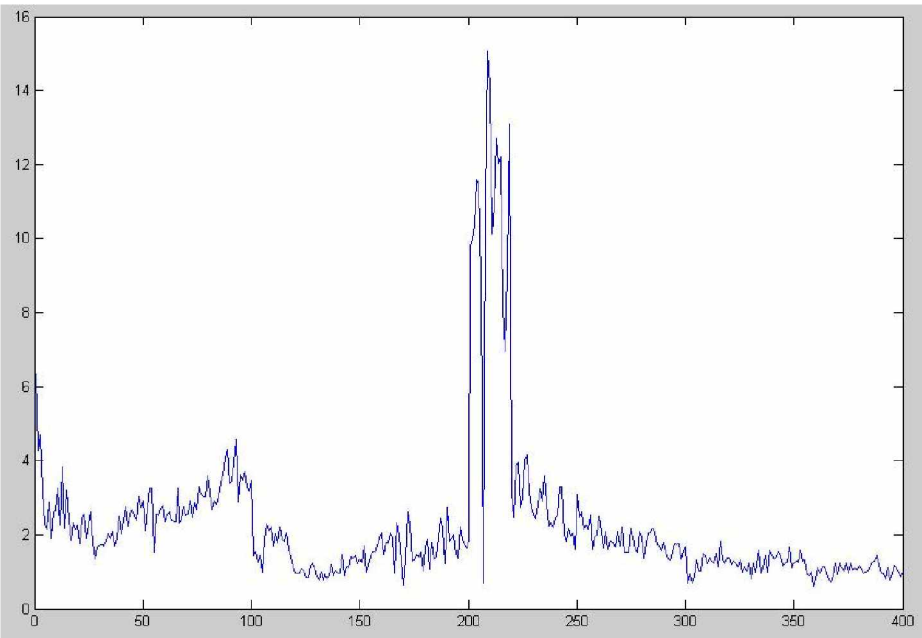


Fig. 6.6 Variation of WL

Incorporating the features shown in the figures - the signal can be separated into four sets:

- The first set of 100 points from the variation curves represent the close motion done by the first subject under observation

- The next set of points(101-200) from the variation curves represent the open motion done by the first subject under observation

- The next set of points(201-300) from the variation curves represent the close motion done by the second subject under observation, which contains erronour data set, as we shall conclude and neglect further.

- The next set of points(301-400) from the variation curves represent the open motion done by the second subject under observation.

As it looks, signals from 200 to 220 can not be classified with this traditional approach. It can be due to the false impedance matching between the electrodes and the skin surface. Other possible reason can be bad location of the muscle group. By neglecting these 20 points, from further calculation and analysis, the classified data are ready for processing. I should be able to base my work on improved readings which do not contain any extraneous results or data sets that could lead to an errorfull conclusion. I therefore, intend to achieve better and more precise results tending to actual accurate observations, than the results I achieved by including the erroneous data sets. The algorithm was also implemented on the erroneous data sets with slight modifications, but it did not present the desired results and the points (201-220) were eventually neglected in further processing of the input data to achieve the correct result.

6.4 Flow diagram for EMG analysis

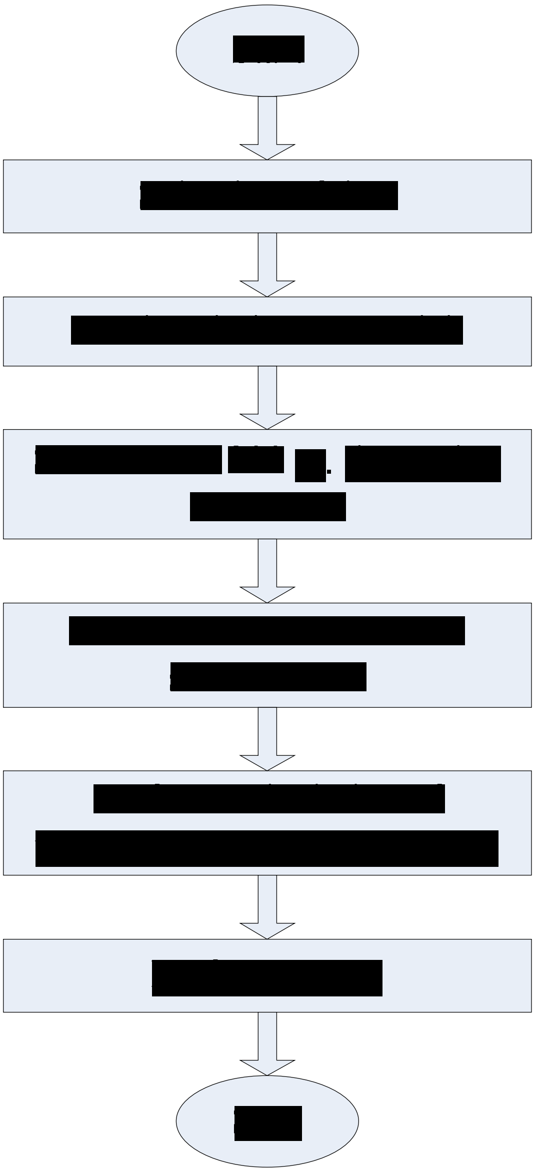


Fig. 6.7 EMG analysis

7. FUZZY LOGIC

Fuzzy logic was first developed in 1965 by Lotfi Zadeh. Over the last decade fuzzy sets and fuzzy logic have been used in a wide range of aplications including process control, image processing, classifications, management, economics, pattern recognition and decision making. Specific applications include washing-machine automation, camcoder focusing, TV colour tuning, automobile transmission and subway operations. It provides an approximate but effective means of describing behavior of systems that are too complex, ill-defined or not easily analyzed mathematically. Fuzzy variables are processed using a system called fuzzy logic controler. It involves fuzzyfication, fuzzy inference and defuzzyfication. The fuzzyfication process converts a crisp input value to a fuzzy value. The fuzzy inference is responsible for drawing colclusions from the knowledge base. The defuzzyfication process converts the fuzzy control actions into a crisp control action.

Fuzzy logic uses graded statements rather than ones that are strictly true or false. Thus, fuzzy logic provides an approximate but effective way of describing the behavior of systems that are not easy to descrive precisely. Fuzzy logic controllers are extensions of the common expert systems that use production rules like 'if-then'. The result is that fuzzy logic can be used in controllers that are capable of making intelligent control decisions in sometimes volatile and rapidly changing problem environtments.

7.1 Fuzzy Inference System (FIS)

Fuzzy Inference System (FIS) play a important role in the induction of rules from observations. It makes fuzzy logic an effective tool for the conception and design of intelligent systems. Conventional FIS models (like Mamdani or Sugeno) are usually limited to special cases of greather than or less than membership functions. In my work I use Mamdani type model, because it is more human-like and it is well suited to human input.

7.1.1 Mamdani type FIS

A Mamdani type FIS tests each input value against each membership function associated with that input. The outputs from all membership functions in a rule are combined to give the overal firing strength of the rule – usually with using the fuzzy AND function, often the minimum of the membership function output values. The firing strength of the rule then determines the maximum level of the consequent membership function. All the qualified consequents are then aggregated together using, for instance, the max function, to produce the final consequent shape, which is then defuzzified using one of the defuzzification operators, usually centroid of area.

A problem with such a model is its inability to remove output weightings when new information is acquired by a different rule, it may only add weightings in different places in the output range, i.e. it is monotonic. A possible solution to this is the redefinition of the consequent NOT operator [8].

Following steps in my present work:

- selection of the FIS (mamdani)
- define number of input and output (5 input & 2 output)
- fuzzify the input variables
- define membership functions for each input & output
- develop the if - then rules
- apply these if - then rules on the input to get the output
- defuzzify the fuzzy output into class output

7.2 Flow diagram for Fuzzy Inference System (FIS)

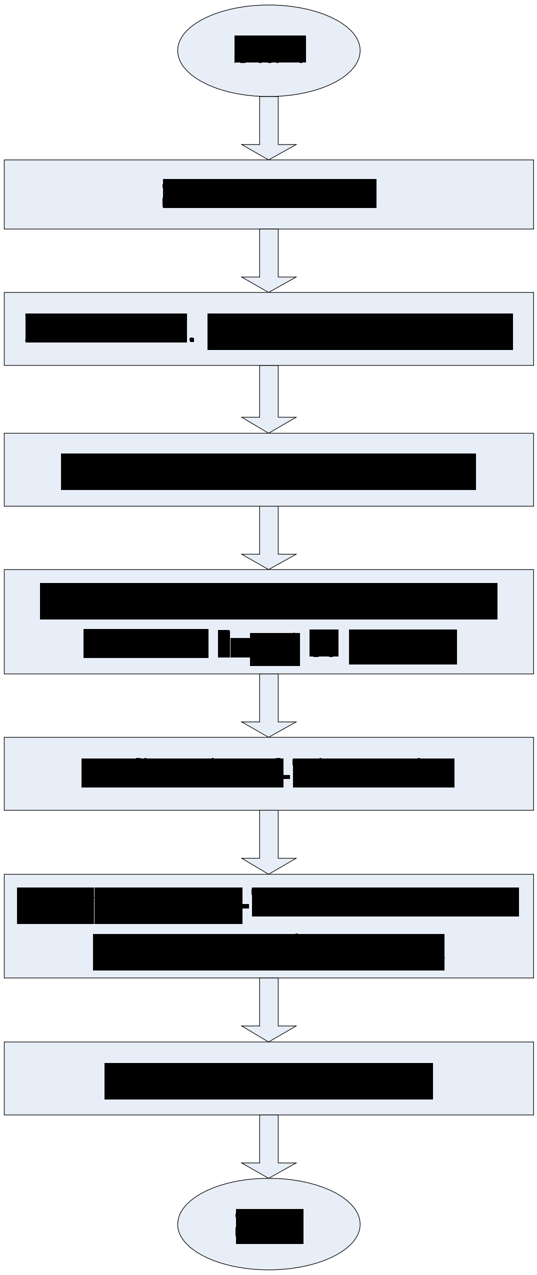


Fig. 7.1 Fuzzy Inference System (FIS)

7.3 Results and Discussion

The Mamdani FIS (fuzzy inference system) was created. Eleven if-then rules were made based on minimum and maximum values of feature values, with three membership functions (low, medium and high), for the input, and two membership functions (open and close) for the output. Overall classification rate came out as 82.75 %. This is the best accessible rate, with a 100% probability for close motion detecting (each guy) and 65.5 % for open motion detecting (45% for the Subject1 and 86 % for the Subject2). To access this rate, I did not form if-then rules for ZC and SSC. If I would have applied SSC to the system, for improving the open rate detection, i would have got a 5% higher probability for this motion (70.5% overall), but on the other hand I would have got 35.5 % less rate for close motion (64.5% overall).

After the analysis of all these parameters for the whole data set, it is found, that there is no significant variation of Zero crossing (ZC) and Slope-sign change (SSC) for this motion - these features should be useful for analysis of other kinds of motion – and are hence not included in the feature vector.

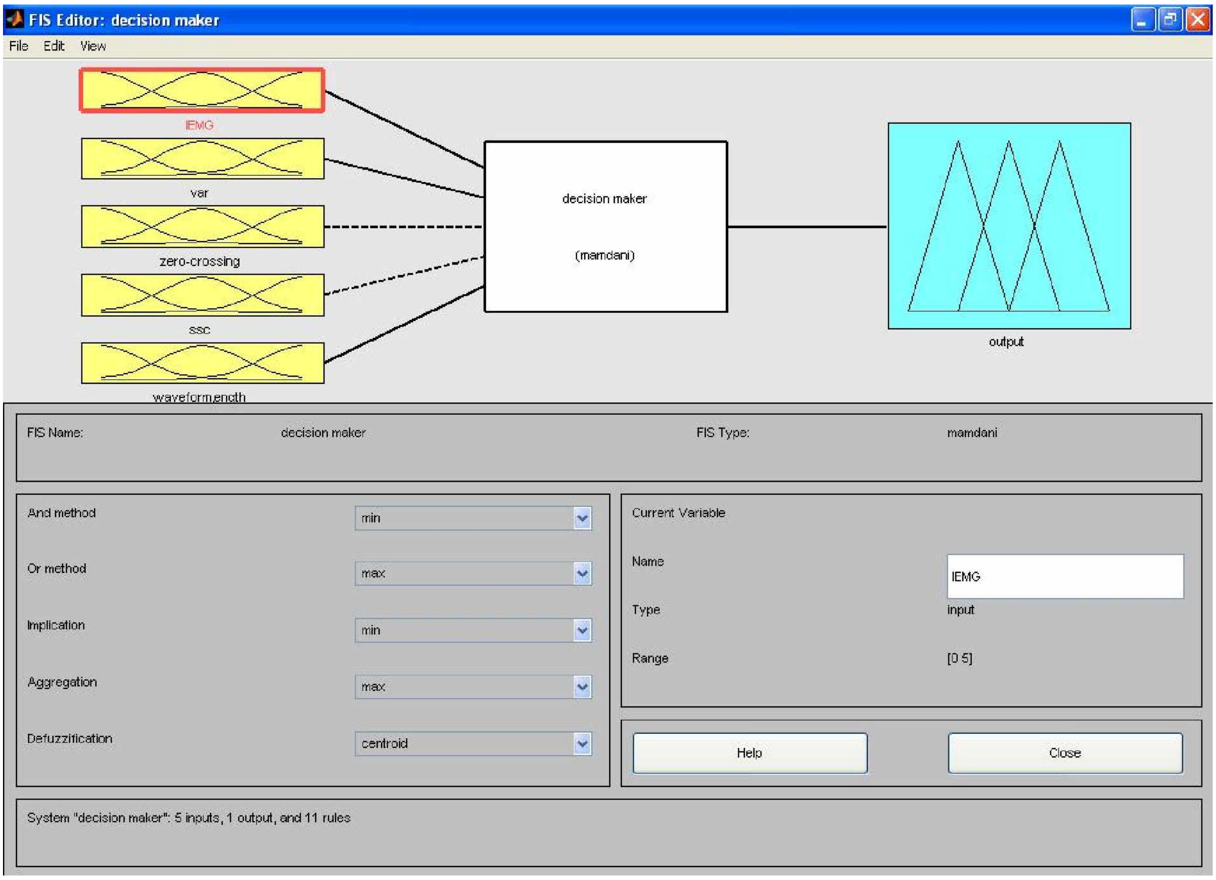


Fig. 7.2 My Fuzzy Inference System - decision maker

8. CONCLUSION

Within the scope of bachelor work I have tried to investigate the methods for classification of different grasp motions – open or close – for the wrist, on the basis of recorded EMG data analysis. EMG data was recorded with a Biopac MP35 acquisition unit with the help of three electrodes placed on skin surface – two to the muscles Flexor Carpi Radialis and Extensor Carpi Radialis Brevis (Fig. 5.1) and the third on the foreleg (Earthed electrode). Altogether 400 signals were recorded, 200 for close motion and another 200 for open motion.

The recorded Biopac platform based data was changed to .txt, which is a usable data format for Matlab. Data was then saved to four data files, named after the 'donors' and the motion kind, for easier transparency and information retrieval. As the next step, a 200 point long data was selected (filtered) from usable data range for each signal using threshold (Fig. 5.7). From these data, I made a 400 x 200 main matrix.

With the help of Matlab, traditional parametric features such as Integrated EMG (IEMG), Variance (VAR), Zero-Crossing (ZC), Slope-Sign Change (SSC) and Waveform Length (WL) were calculated and saved to another matrix. Using these signals (Fig. 6.2, 6.3, 6.4, 6.5, 6.6) it is easy to deduce that variations between 200 and 220 are much bigger than the others, which can be due to the inaccuracy of the threshold allocated, and for this reason these were not been included to the next step.

The last task was to choose and create a Mamdani type FIS (Fuzzy Inference System) in Matlab (Fig. 7.2). Eleven if-then rules were made by virtue of minimum and maximum of feature values, with three membership functions (low, medium and high) for input and two membership functions (open and close) for the output. After running the feature values matrix through the FIS, and forming the output membership functions, an overall classification rate of 82.75 % has been achieved which is acceptable.

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LIST OF FIGURES