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Table of content

Abstract

Advanced forearm prosthetic devices employ classifiers to recognize different electromyography (EMG) signal patterns, in order to identify the user's intended motion gesture. The classification accuracy is one of the main determinants of real-time controllability of a prosthetic limb and hence the necessity to achieve as high an accuracy as possible. In this study two EMG channels (Delsys DE 2.x series EMG sensors) signal were used to classify hand finger movements. Ten classes of individual and combined fingers movements were implemented including: the flexion of each of the individual fingers, i.e., Thumb (T), Index (I), Middle (M), Ring (R), Little (L) and the pinching of combined Thumb–Index (T–I), Thumb–Middle (T–M), Thumb–Ring (T–R), Thumb–Little (T–L), and finally the hand close (HC) . The finger movements were also classified by using different learning algorithms. The best classification was performed by using svm achieved an average classification accuracy of 97%. The svm-based classifier aims to classify ten individual and combined fingers motion command into one of the predefined set of movements.

Prior to classification, EMG data is segmented with a sliding window technique and time domain features such as Mean Absolute Value (MAV), Root Mean Square (RMS), Waveform Length (WL) and wavelet decomposition are extracted for each window and combined to a feature set. Extracted features are used as inputs to the classification system. Feature sets are extracted and projected in a manner that ensures maximum separation between the finger movements and then fed to two different classifiers. Then apply the classification Algorithm (svm). Several window sizes that affect the classification performance have been reported. The best feature set that ensures maximum discrimination between the finger movements has also been reported. Validation shows that svm can classify EMG signals correctly with a higher classification rate suitable for designing prosthetic and assistive devices.

Keywords: Electromyography signal, EMG, Classification, wavelet decomposition, Mean absolute value, root mean square, Waveform Length.

CHAPTER 1

1. INTRODUCTION

1.1.OVERVIEW

The loss of the human forearm is a major disability that profoundly limits the everyday capabilities and interactions of individuals with upper-limb amputation the interaction capability with the real-world can be restored using myoelectric control, where the Electromyogram (EMG) signals generated by the human muscles are used to derive control commands for powered upper-limb prostheses. Typically a pattern recognition framework is utilized to classify the acquired EMG signals into one of predefined sets of forearm movements.

1.2.OBJECTIVES

The main objective of this study is to develop a control system, based on EMG signals, able to detect and interpret different user hand movements to operate a printable bionic hand. In order to achieve this, the program must fulfill the following aspects:

1. Acquire and process EMG signals.
2. Identify the specific movement underneath the processed EMG data.
3. Be sensitive to changes in position.
4. Real-time actuation of the five-fingered robotic hand.
5. Integration of the different elements: robotic hand, EMG circuit and control system.
6. Low cost

1.3. STRUCTURE

The dissertation starts with an overview of the EMG theory and related work done in EMG control systems. EMG theory focuses on the physiology and acquisition of the signal. In next chapters, the state of the art of EMG signal processing is analyzed, including data segmentation, feature extraction, dimensionality reduction and data classification.

Next chapters describe the materials and methods used in program development. The EMG acquisition system is assessides basic physiological and biomechanical studies, describing the employed circuit, micro-controller and acquisition software. A detail explanation of the control system functioning can be followed step by step through:

- EMG acquisition method
- preprocessing methods
- Segmentation and feature extraction
- Dimensionality reduction
- Generation and training of the Neural Network "svm"
- Integration of the control system with the printed robotic hand""

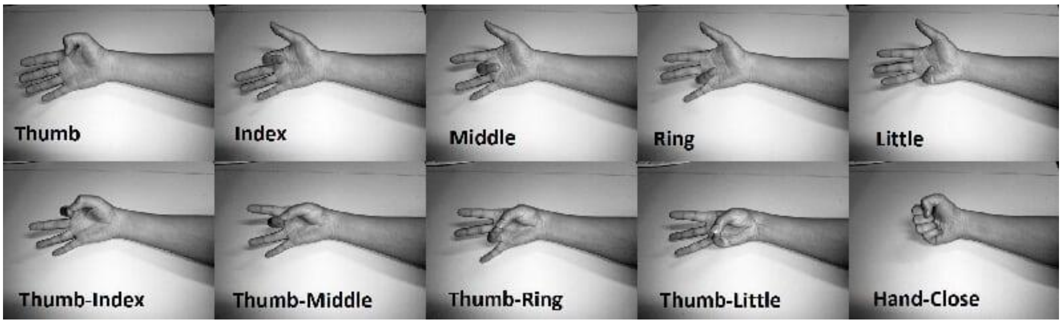
The thesis concludes with the results of the performed tests and the conclusions and future work extracted from their analysis.

1.5. DATASETS

In dataset, eight subjects, six males and two females, aged between 20 and 35 years were recruited to perform the required fingers movements. The subjects were all normally limbed with no neurological or muscular disorders. All participants provided informed consent prior to participating in the study. Subjects were seated on an armchair, with their arm supported and fixed at one position to avoid the effect of different limb positions on the generated EMG signals (Scheme, Founger, Stavdahl, Chan, & Englehart, 2010). The EMG data was collected using two EMG channels (Delsys DE 2.x series EMG sensors) and processed by the Bagnoli Desktop EMG Systems from Delsys Inc. A 2-slot adhesive skin interface was applied on each of the sensors to firmly stick the sensors to the skin. A conductive adhesive reference electrode (Dermatrode Reference Electrode) was utilized on the wrist of each subject. The positions of these electrodes are shown in Fig. 1. The EMG signals collected from the electrodes were amplified using a Delsys Bagnoli-8 amplifier to a total gain of 1000. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) was used to sample the signal at 4000 Hz; the signal data were then acquired using Delsys EMGWorks Acquisition software. The EMG signals were then band pass filtered between 20 and 450 Hz with a notch filter implemented to remove the 50 Hz line interference. Ten classes of individual and combined fingers movements were implemented including: the flexion of each of the individual fingers, i.e., Thumb (T), Index (I), Middle (M), Ring (R), Little (L) and the pinching of combined Thumb–Index (T–I), Thumb–Middle (T–M), Thumb–Ring (T–R), Thumb–Little (T–L), and finally the hand close (HC) as shown in fig. 1.

dataset link

(https://onedrive.live.com/?cid=aaa78954f15e6559&id=AAA78954F15E6559%21295&Bsrc=Share&Bpub=SDX.SkyDrive&sc=Photos&authkey=!As_iNPKzgU6LJCU)



CHAPTER 2

2. EMG SIGNAL

2.1. EMG DEFINITION

Definition

Electromyography (EMG) is an electrical recording of muscle activity that aids in the diagnosis of n euromuscular disease.

Purpose

Muscles are stimulated by signals from nerve cells called motor neurons. This stimulation causes el ectrical activity in themuscle, which in turn causes contraction. This electrical activity is detected by a needle electrode inserted into the muscleand connected to a recording device. Together, the electr ode and recorder are called an electromyography machine.EMG can determine whether a particular muscle is responding appropriately to stimulation, and whether a muscleremains inactive when not s timulated.

EMG is performed most often to help diagnose different diseases causing weakness. Although EM G is a test of the motorsystem, it may help identify abnormalities of nerves or spinal nerve roots that may be associated with pain or numbness.Other symptoms for which EMG may be useful include n umbness, atrophy, stiffness, fasciculation, cramp, deformity, andspasticity. EMG results can help de termine whether symptoms are due to a muscle disease or a neurological disorder, and when combined with clinical findings, usually allow a confident diagnosis.

EMG can help diagnose many muscle and nerve disorders, including:

- muscular dystrophy
- congenital myopathies
- mitochondrial myopathies
- metabolic myopathies
- peripheral neuropathies
- radiculopathies
- nerve lesions
- amyotrophic lateral sclerosis
- polio
- spinal muscular atrophy
- ataxias

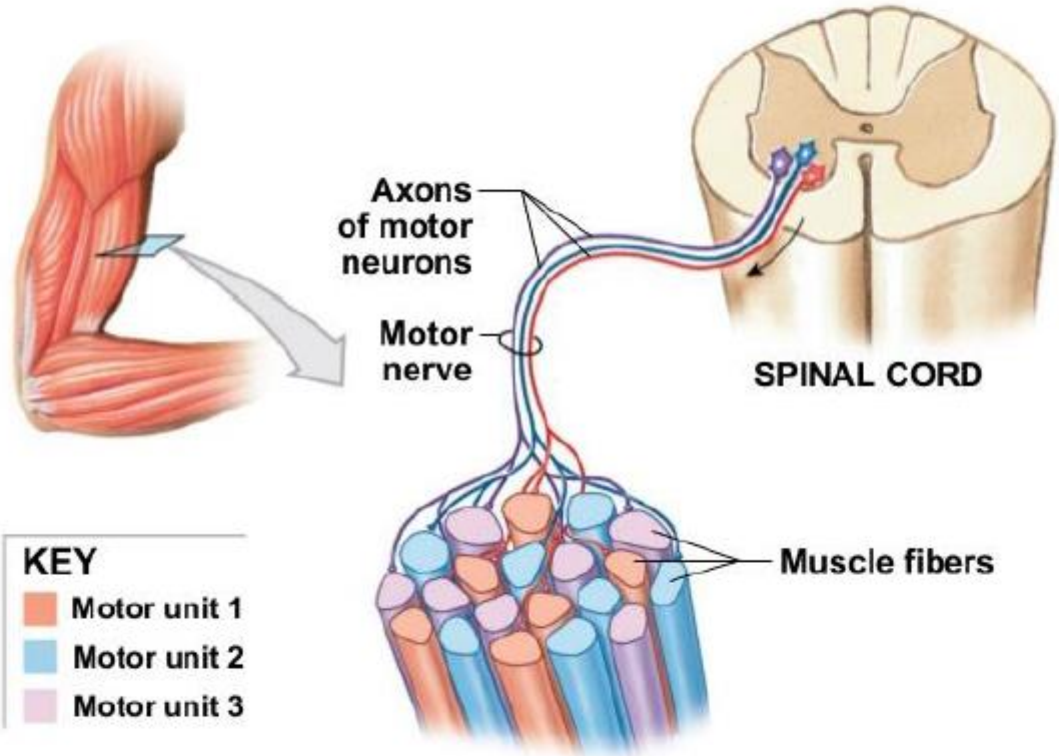
How is an intramuscular EMG done?

A needle is inserted through the skin into the muscle. The electrical activity is detected by this needle (which serves as an electrode). The activity is displayed visually on an oscilloscope and may also be detected audibly with a speaker. Since skeletal muscles are often large, several needle electrodes may need to be placed at various locations to obtain an informative EMG.
After placement of the electrode(s), the patient may be asked to contract the muscle (for example, to bend the leg).

The presence, size, and shape of the wave form (the action potential) produced on the oscilloscope provide information about the ability of the muscle to respond to nervous stimulation. Each muscle fiber that contracts produces an action potential. The size of the muscle fiber affects the rate (how frequently an action potential occurs) and the size (the amplitude) of the action potential.

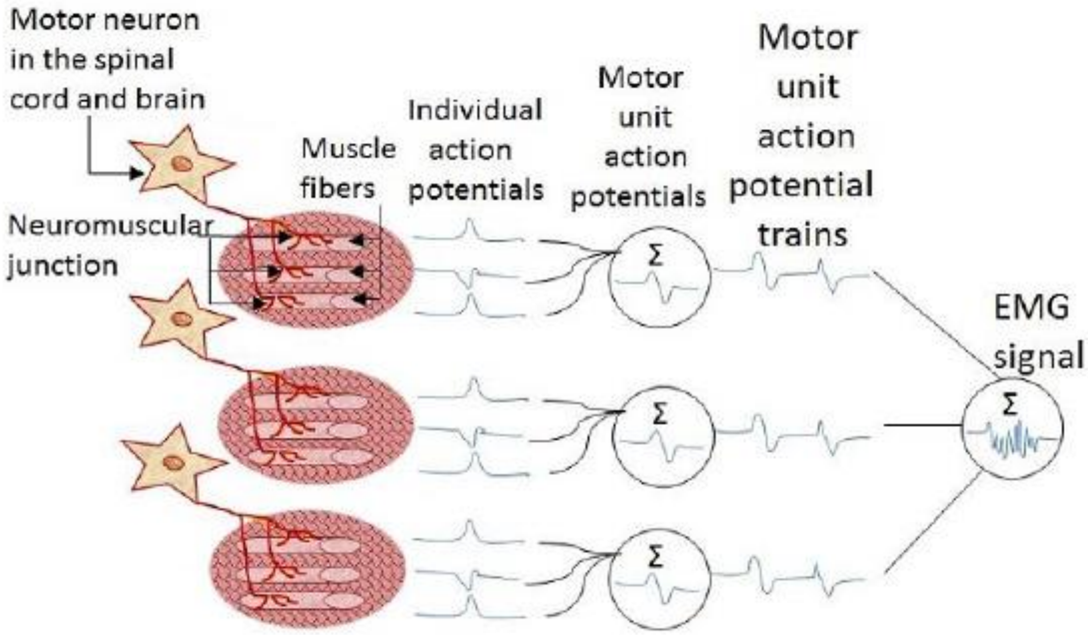
2.2. Physiology

To understand how movement is generated in the body, it is important to know the basic structure responsible for it first. Motor units are the smallest functional modules that explain muscle contraction through neural control. They are formed by a motor neuron and all the skeletal muscle fibers it stimulates. These fibers are intermingled with other motor unit muscle fibers without following any distribution pattern. Motor neurons propagate electrical stimuli (action potentials) from the central nervous system to the muscle fibers Fig.2.



If muscle fibers are not activated, there is an ionic equilibrium (resting potential) between the inner and outer spaces, established at -80 to -90 mV. However, when an action potential reaches the axon terminal of a motor neuron, it triggers the release of a neurotransmitter at the neuromuscular junction. This neurotransmitter opens $Na+$ channels, favoring the inflow of these cations, increasing the membrane potential up to +30 mV and thus, causing the depolarization of the membrane. This condition is immediately compensated by $Na+/K+$ ion pumps that repolarize the membrane to the original value. The effect of the action potential is muscle contraction, being an electro-mechanical coupled process. The electromagnetic field produced by ion movement, can be detected and recorded with electrodes placed near the muscles.

So far, how a single muscle fiber is stimulated by an action potential has been explained. However, a single motor neuron innervates several muscle fibers that contract in unison. The spatial-temporal summation of all the individual action potentials that reach these muscles is referred as Motor Unit Action Potential (MAUP). To maintain muscle contraction, successive activation of motor units is required. This sequence of MUAP form the Motor Unit Action Potential Train (MUAPT). As previously mentioned, different motor unit fibers assemble muscles. Therefore, movement involves the activation of multiple motor units. The recorded EMG signal is the superposition of MUAPTs corresponding to the activated motor units Fig.3.



2.3. **EMG APPLICATION**

Applications of EMG or the usage of EMG in fields:

1. Medical Research

- Orthopedic
- Surgery
- Functional Neurology
- Gait & Posture Analysis

2. Rehabilitation

- Post-surgery/accident
- Neurological Rehabilitation
- Physical Therapy
- Active Training Therapy

3. Ergonomics

- Analysis of demand
- Risk Prevention
- Ergonomics Design
- Product Certification

4. Sports Science

- Biomechanics
- Movement Analysis
- Athletes Strength Training
- Sports Rehabilitation

2.4. EMG Types

Why is EMG measured and studied?

As far as we're concerned for the purposes of this manual, EMG contains two types of important information, timing of muscle activity and its relative intensity. Other information is also present (e.g. frequency spectrum and acoustic information) but most clinical diagnostic reports are based on the muscle activity and intensity components of the EMG signal. This information can be used within a wide variety of fields of study:

- Numerous neuromuscular disorders may present aberrant EMG signals while performing functional tasks like posture and locomotion. This may be any combination of inappropriate muscle activation or errors in muscle activation intensity.

- Biomedical engineers often use EMG signals to derive volitional control of an artificial limb or brace through the interpretation of the EMG signal.

- Biomechanists and other scientists can study the balance mechanism by which humans maintain postural stability in the presence of perturbations.

- Gait analysis laboratories study the precise control of the musculoskeletal system during ambulation or other complex human movements.

- Doctors often evaluate the temporal sequence of the recorded activity to address questions of CNS control. Often called "nerve conduction", this is a rapidly growing field of study that is quite separate from the multi-channel, muscle activation studies that this manual addresses.

- Researchers study multi-channel EMG data together with biomechanical parameters, such as muscle force to investigate the relationships between different muscle contractions.

- EMG alone can be used to differentiate normal gait from pathologic gait by comparing recorded EMG timing to the normal EMG timings for a given subject population for any gait activity.

For the purposes of this manual, there are two main types of electromyography:

Clinical EMG – sometimes called "diagnostic EMG" or "Nerve Conduction EMG" is typically done by physiatrists and neurologists. This is the study of the characteristics of the motor unit action potential for duration and amplitude. These studies are typically done to help diagnostic neuromuscular pathology. They also evaluate the spontaneous discharges of relaxed muscles and are able to isolate single motor unit activity. Generally, these types of studies focus on a single muscle or group of muscles.

Kinesiological EMG – this is the type most often found in the literature regarding movement analysis. This type of EMG examines the relationship of muscular function to movement of the body segments and evaluates timing of muscle activity with regard to the movements. Additionally, many studies attempt to examine the strength and force production of the muscles themselves. Kinesiological EMG almost invariably looks at the actions, and interactions, of several muscles simultaneously.

Both the EMG Analysis and EMG Graphing software applications focus almost exclusively on providing information from the viewpoint of Kinesiological EMG studies that involve multiple muscle contractions during physical activity. As a result, the rest of this manual will discuss EMG from a Kinesiological point of view.

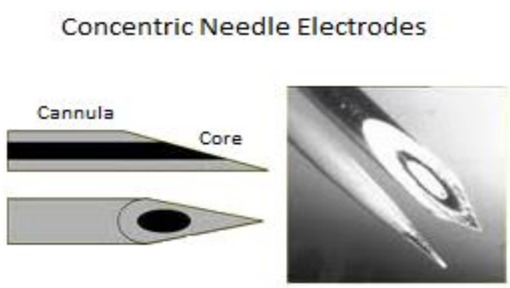
2.5. EMG Acquisition

2.5.1. EMG electrodes and its types

The bioelectrical activity inside the muscle of a human body is detected with the help of EMG electrodes. There are two main types of EMG electrodes: surface (or skin electrodes) and inserted electrodes. Inserted electrodes have further two types: needle and fine wire electrodes. The three electrodes (needle, fine wire and surface) are explained as follows. Among these three electrodes, surface EMG electrodes will be specifically discussed in detail as it pertains to the topic of this chapter.

2.5.1.1. Needle electrodes

Needle electrodes are widely used in clinical procedures in neuromuscular evaluations. The tip of the needle electrode is bare and used as a detection surface. It contains an insulated wire in the cannula. The signal quality from the needle electrodes is comparatively improved from other available types. Needle electrodes have two main advantages. One is that its relatively small pickup area enables the electrode to detect individual MUAPs during relatively low force contractions. The other is that the electrodes may be conveniently repositioned within the muscle (after insertion) so that new tissue territories may be explored A needle electrode is shown in Fig.4.



2.5.1.2. Fine wire electrodes

Wire electrodes are made from any small diameter, highly non-oxidizing, stiff wire with insulation. Alloys of platinum, silver, nickel, and chromium are typically used. Wire electrodes are extremely fine, they are easily implanted and withdrawn from skeletal muscles, and they are generally less painful than needle electrodes whose cannula remains inserted in the muscle throughout the duration of the test . A fine wire electrode is shown in Fig.5.

2.5.1.3. Surface EMG electrode

Surface EMG electrodes provide a non-invasive technique for measurement and detection of EMG signal. The theory behind these electrodes is that they form a chemical equilibrium between the detecting surface and the skin of the body through electrolytic conduction, so that current can flow into the electrode.

These electrodes are simple and very easy to implement. Application of needle and fine wire electrodes require strict medical supervision and certification. Surface EMG electrodes require no such formalities. Surface EMG electrodes have found their use in motor behavior studies, neuromuscular recordings, sports medical evaluations [9] and for subjects who object to needle insertions such as children. Apart from all this, surface EMG is being increasingly used to detect muscle activity in order to control device extensions to achieve prosthesis for physically disabled and amputated population. Surface EMG has some limitations as well. Since these electrodes are applied on the skin, hence, they are generally used for superficial muscles only. Crosstalk from other muscles is a major problem. Their position must be kept stable with the skin; otherwise, the signal is distorted.

2.5.1.3.1. Types of EMG Electrodes

There are two types of surface EMG electrodes: Gelled and Dry EMG electrodes .

2.5.1.3.1.1. Gelled EMG Electrodes

Gelled EMG electrodes contain a gelled electrolytic substance as an interface between skin and electrodes. Oxidation and reduction reactions take place at the metal electrode junction. Silver – silver chloride (Ag-AgCl) is the most common composite for the metallic part of gelled electrodes. The AgCl layer allows current from the muscle to pass more freely across the junction between the electrolyte and the electrode. This introduces less electrical noise into the measurement, as compared with equivalent metallic electrodes (e.g. Ag). Due to this fact, Ag-AgCl electrodes are used in over 80% of surface EMG applications . Disposable gelled EMG electrodes are most common; however, reusable gelled electrodes are also available. Special skin preparations and precautions such as (hair removal, proper gel concentration, prevention of sweat accumulation etc.) are required for gelled electrodes in order to acquire the best possible signal. Gelled EMG electrodes are shown in Fig.6.

2.5.1.3.1.2. Dry EMG electrodes

Dry EMG electrodes do not require a gel interface between skin and the detecting surface. Bar electrodes and array electrodes are examples of dry electrodes. These electrodes may contain more than one detecting surface. In many examples, an in-house pre-amplification circuitry may also be employed in these electrodes. A reusable bar electrode is shown in Fig.7. Dry electrodes are usually heavier (>20g) as compared to gelled electrodes (<1g). This increased inertial mass can cause problems for electrode fixation; therefore, a material for stability of the electrode with the skin is required .

2.5.2. EMG electrode placement and signal acquisition technique

Surface EMG is relatively easy to use as compared to other EMG electrodes. This is the reason why it is being extensively used in the control of robotic mechanisms to achieve prosthesis. It is also widely used in latest EMG researches by engineers as no medical certification or expertise is required for its application. Its use in rehabilitation prosthesis is favorable as it does not cause any kind of discomfort to the subject on whom it is applied. Other kinds of EMG electrodes (needle and fine wire), when inserted into the skin of the subject, may effect a twitching sensation and cause him or her to make movements. In order to get the best results from SEMG, it is really important to have a proper understanding of the muscles from which the EMG signal is being extracted. The placement on skin also requires adequate study and requires skin preparation beforehand as well. The EMG electrodes, their types, sub-types and categories have already been explained in detail in the previous section. Since, our concern is only with Surface EMG (SEMG), hence, we will only deal with the placement and signal acquisition technique using surface EMG electrodes.

2.5.2.1. Skin preparation

General considerations the quality of an EMG measurement strongly depends on a proper skin preparation and electrode positioning. The main strategy of skin preparation is stable electrode contact and low skin impedance. Most modern EMG-amplifiers are designed for skin impedance levels between 5 and 50 k Ohm (between pairs of electrodes). Usually it is necessary to perform some skin preparation before the electrodes can be applied. There are no general rules for it and several possibilities to reach a good skin condition for EMG-measurements exist. Especially for beginners it will be of great value to check the quality of the chosen method by measuring the actual impedance resistance between electrodes with a regular multi-meter or specialized impedance meters (see chapter Signal Check Procedures). Another important consideration is the targeted test condition and exercise. If a somewhat static or slow motion movement is planned (e.g. a clinical muscle function test) and the basic analysis idea is qualitative (amplitude changes in terms of more/less), a simple alcohol cleaning may be sufficient. If very dynamic conditions with risk of movement artifacts (e.g. fast walking, running or other highly accelerated movements is planned), a very thorough preparation is imperative.

Skin preparation procedures

The following procedures may be considered as steps to prepare the electrode application:

1) Removing the hair:

This is needed to improve the adhesion of the electrodes, especially under humid conditions or for sweaty skin types and/or dynamic movement conditions.

2) Cleaning of the skin:

Method A:

Special abrasive and conductive cleaning pastes are available which remove dead skin cells (they produce high impedance) and clean the skin from dirt and sweat.

Method B:

Alternatively a very find sand paper can be used: A soft and controlled pressure in 3 or 4 sweeps usually is enough to get a good result. Attention: Avoid any harm to the skin from rubbing too hard! The use of sand- paper should be combined skin with an alcohol pad.

Method C:

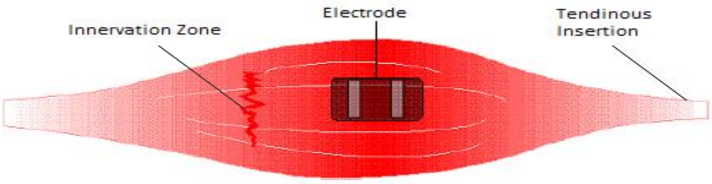
The pure use of alcohol may be another alternative if used with a textile towel (that allows soft rubbing). This latter method may be sufficient for static muscle function tests in easy conditions. Whichever skin preparation method and electrode application technique is used, when done properly, the skin typically receives a light red color. This indicates good skin impedance condition.

2.5.2.2. EMG electrode placement

The application of EMG electrodes requires adequate know how of the skeletal muscles. The EMG electrode placement will be discussed in detail under this section. In most cases, two detecting surfaces (or EMG electrodes) are placed on the skin in bipolar configuration . In order to acquire the best possible signal, the EMG electrode should be placed at a proper location and its orientation across the muscle is important. The surface EMG electrodes should be placed between the motor unit and the tendinous insertion of the muscle, along the longitudinal midline of the muscle . The distance between the center of the electrodes or detecting surfaces should only be 1-2 cm. The longitudinal axis of the electrodes (which passes through both detecting surfaces) should be parallel to the length of the muscle fibers.

As mentioned previously, the EMG detecting surfaces should be placed in between the motor unit and the tendon insertion of the muscle. Detecting surfaces placed on the belly of the muscle has proved to be a more than acceptable location. Here, the target muscle fiber density is the highest. Fig.8 shows the proper EMG electrode placement. When the electrodes are arranged in this way, the detecting surfaces intersect most of the same muscle fibers, and as a result, an improved superimposed signal is observed.

The electrodes should not be placed elsewhere. In the past, a misconception prevailed that the EMG detecting surfaces should be placed on the motor unit. But, as a matter of fact, the electrode location on the motor point serves as the worst location for signal detection. Similarly, the electrodes should neither be placed at or near the tendon nor at the edge of the muscle. The muscle fibers become thinner and smaller in number when they approach the tendon of the muscle resulting in a weak EMG signal, proving the fact that electrode placement near the tendon is not feasible. If the electrode is placed at the edge of the muscle, the chances of crosstalk from other muscles will considerably increase, and the resultant signal will be disturbed by those of other muscles Fig.8.The ideal position of the electrode (two detecting surfaces) is between the innervation zone (or motor unit) and the tendinous insertion (or belly of the muscle)



2.5.2.2. Number of electrodes

The optimal number of electrodes for sEMG interfaces hasmostly been studied by placing the electrodes on the forearm. In laboratory conditions, the increase in classifi-cation accuracy has become saturated with three to four bipolar channels. A relatively small number of electrodes have beenshown to be sufficient also when electrode shifts are present: therecommended subset is four to six bipolar channels, of which onehalf were longitudinal channels and the other half transverse channels. However, the optimal number of electrodes may alsodepend on individual anatomy of the subject. Andrews et al.]increased the number of bipolar channels from one to eight, andfor four subjects the classification accuracy remained very pooruntil increased sharply when the number of channels was fiveor seven. For eight subjects, the classification accuracy increasedsignificantly up to three electrodes. The classification was testedduring a typing task with the classification system optimized indi-vidually for each subject.When incrementally adding new channels, the channels thatgave the best classification accuracy for small subsets were rel-atively far from each other, as would be expected because theyprovide most new information to the classifier. Wheregross hand and forearm postures have been studied, the optimalelectrode subset usually includes electrodes placed approximatelyon flexor digitorum superficials, flexor capri ulnaris, extensor capriradialis longus or brevis, and extensor capri ulnaris, whereaswhen studying finger movements, the selected electrodes were placed were placed approximately on flexor digit rum prefunds and extensor digitorum communis. The drawback of small number of electrodes is that the fault of only one electrode can cause significant degradation in classification accuracy. The malfunctioning channels (e.g. due tobad skin–electrode contact) can be automatically detected and removed, but re-training of the classifier is still needed. HD-sEMG relying on spatial-domain information (e.g. experimentalvariogram) could solve this problem since HD-sEMG has shown to be capable to maintain high performance even without re-training when some electrodes are omitted. The drawbacks of HD-sEMG based systems are increased production costs and computational demands. However, the drop in performance has shown to be relatively small when the number of electrodes used in the training of the classifier is reduced from 96 to 24. The development of more powerful microprocessors enables the use of HD-sEMG. Moreover, it has been shown that e-textiles can be used in HD-sEMG systems, and thus are easy to apply, are non-obtrusive and allow a classification accuracy of ∼90% for nine hand and wrist postures.

2.5.3. Electrical design considerations

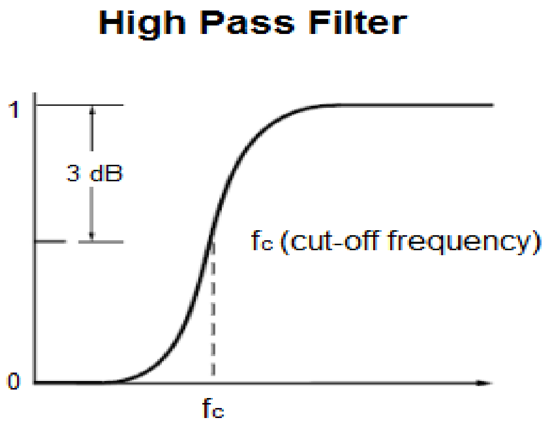
This section will discuss the electrical design considerations in order to synthesize the best possible EMG signal from the muscles of the human body in thorough detail. The basic circuitry for signal acquisition or preamplification circuitry is explained in due detail in the previous section. In this section we will discuss the circuitry implemented after the preamplification stage.

1. Filtering

As discussed earlier, there are many concerns regarding the proper detection of the EMG signal. Once the electrode is properly placed and the signal is extracted, noise plays a major role in hampering the recording of the EMG signal. For this purpose, the signal has to be properly filtered, even after differential amplification. The noise frequencies contaminating the raw EMG signal can be high as well as low. Low frequency noise can be caused from amplifier DC offsets, sensor drift on skin and temperature fluctuations and can be removed using a high pass filter. High frequency noise can be caused from nerve conduction and high frequency interference from radio broadcasts, computers, cellular phones etc. and can be deleted using a low pass filter. In order to remove these high and low frequencies, high pass and low pass bio-filters will be discussed in adequate detail in this section.

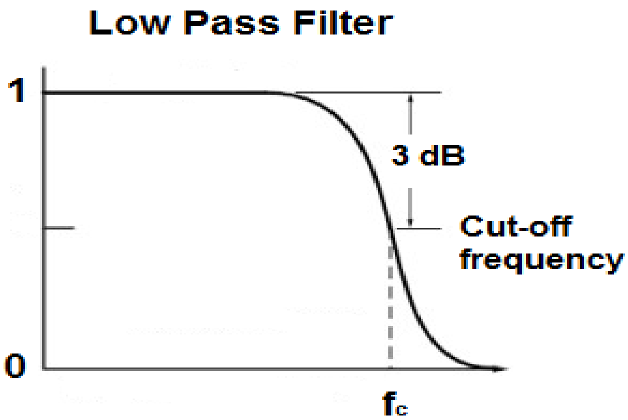
1.1. High pass filter

A high pass filter is used to remove low frequency component from a particular electrical signal. A term ‘cut-off frequency’, denoted by ‘fc’, is the frequency below which all frequencies are eliminated. All frequencies above fc are carried forward. The frequency range where the filter response is ‘1’ and the signals are transmitted is known as ‘pass band’ region. On the contrary, the frequency range where the filter response is ‘0’ and the signals are attenuated is known as ‘stop band’ region. A high pass filter response is shown in Fig.9.



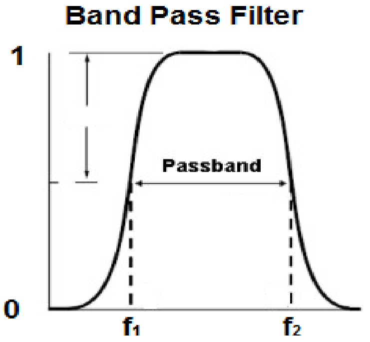
1.2. Low pass filters

The concept of low pass filters is entirely opposite to that of high pass filters. In these filters, the frequencies less than the cut-off frequency are transmitted and above that are removed. A low pass filter response is shown in Fig.10.



1.3. Bandpass filtering for EMG

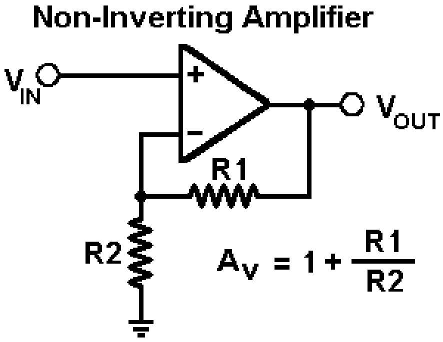
As mentioned previously, for the transmission of pure EMG, the high and low frequency noise should be deleted. For this purpose, only a specific band of frequency should be carried forward. This can be made possible with the help of a band pass filter. A band pass filter response is shown in Fig.11.



The frequency region where the response of the EMG signal is '1' is called the 'passband' and in the case of band pass filter, it is between f1 and f2. A band pass filter can be designed by connecting a low pass and a high pass filter in series. By selecting proper values of R and C, we can develop a band pass filter which can carry forward the most effective component of the EMG signal. It is recommended that for EMG, f1 should be 65-70 Hz and f2 be 150-180 Hz.

2. Amplification

After the signal has been filtered properly and a suitable band of EMG frequency is obtained, the next stage is amplification. The EMG signal obtained has to be powered up to a suitable level. The amplification of the EMG signal can be easily carried out with the help of a non-inverting amplifier, shown in Fig.12. The gain of the amplifier is provided in the figure as 'Av'. The non-inverting amplifier is only used when the signal is being received from a single wire referenced to ground. Amplification can be done in stages in order to cater for chip requirements, by cascading them in series. The EMG signal, as mentioned before, is very weak i.e. only 1-10 mV. For certain muscles, for which the signal response is very strong e.g. Biceps Brachii, a gain of 500-1000 can be enough. But for muscles, whose EMG response is weak e.g. Flexor Palmaris Longus (ring finger muscle), the gain settings should be very high i.e. 10000. The proper gain setting solely depends upon the signal response observed from the subject's target muscle. It is to be noted that every subject gives a separate signal response. Some subjects will give weak responses as compared to others. So, in that case, appropriate gain value should be set once the subject's EMG signal response is properly observed.



2.6. EMG History

The development of EMG started with Francesco Redi's documentation in 1666. The document informs that highly specialized muscle of the electric ray fish generates electricity. By 1773, Walsh had been able to demonstrate that Eel fish's muscle tissue could generate a spark of electricity. In 1792, a publication entitled "De Viribus Electricitatis in Motu Musculari Commentarius" appeared, written by A. Galvani, where the author showed that electricity could initiate muscle contractions . Six decades later, in 1849, Dubios-Raymond discovered that it was also possible to record electrical activity during a voluntary muscle contraction. The first recording of this activity was made by Marey in 1890, who also introduced the term *electromyography*. In 1922, Gasser and Erlanger used an oscilloscope to show the electrical signals from muscles. Because of the stochastic nature of the myoelectric signal, only rough information could be obtained from its observation. The capability of detecting electromyographic signals improved steadily from the 1930s through the 1950s and researchers began to use improved electrodes more widely for the study of muscles. Clinical use of surface EMG for the treatment of more specific disorders began in the 1960s. Hardyck and his researchers were the first (1966) practitioners to use sEMG. In the early 1980s, Cram and Steger introduced a clinical method for scanning a variety of muscles using an EMG sensing device .

It is not until the middle of the 1980s that integration techniques in electrodes had sufficiently advanced to allow batch production of the required small and lightweight instrumentation and amplifiers. At present a number of suitable amplifiers are commercially available. In the early 1980s, cables became available which produce artifacts in the desired microvolt range. During the past 15 years, research has resulted in a better understanding of the properties of surface EMG recording. In recent years, surface electromyography is increasingly used for recording from superficial muscles in clinical protocols, where intramuscular electrodes are used for deep muscle only.

There are many applications for the use of EMG. EMG is used clinically for the diagnosis of neurological and neuromuscular problems. It is used diagnostically by gait laboratories and by clinicians trained in the use of biofeedback or ergonomic assessment. EMG is also used in many types of research laboratories, including those involved in biomechanics, motor control, neuromuscular physiology, movement disorders, postural control, and physical therapy.

CHAPTER 3

3. Preprocessing

The electromyography (EMG) signal energy is limited in the frequency range from 0 to 500 Hz. Further, noise due to motion artefacts had most of their power in the frequency range 0 to 20 Hz. Accordingly, the EMG signals were band pass-filtered (20–500 Hz) through a fourth order Butterworth filter. Due to the random nature of the EMG signal, the instantaneous value of the EMG signal is not suitable for control purposes. Consequently, SEMG signals were segmented using moving windows for data analysis. Two types of windows, including overlapped and disjoint windows, have been proposed in the literature. Steps of preprocessing Fig.13.

3.1. Data Segmentation

The EMG signal has two states: transient and steady. In the transient state, the muscle goes from rest to a voluntary contraction level. Constant contraction of the muscle can be seen under the steady state. In addition the EMG signal in the transient state shows a large deviation of error compared to the steady state level. Therefore, in many cases, the steady state signal is used for the analysis of EMG. For the better result of data segmentation, the selected time slot should be equal to or less than 300ms. This includes segment length and processing time to generate the control command. In addition bias and variance of features can be minimized by selecting adequately a large time slot and it contributes to better classification performance. Data segmentation is carried out with two major techniques: overlapping segmentation, and disjoint segmentation which uses segments with predetermine length for feature extraction. Also processing time is a small portion of segment length and thus processor is idle for remaining time of the segment. The new segment slides over the current segment and has small incremental time for overlapping segmentation technique. According to, overlapping segment method increases processing time and hence better for the data segmentation.

3.1.1. Windowing technique

There are two alternative windowing techniques: adjacent windowing and overlapped windowing. In the former technique, custom-length consecutive segments are used for analysis and feature extraction. Because of high-speed processors, the processing time is usually less than the duration of time segment, which makes the processor idle for a certain amount of time, as can be seen in Fig.14 (left). Overlapped windowing uses the idle time for acquiring more data to be processed. As Fig.14 (right) illustrates, each segment overlaps the previous one. The overlapped window approach is more appropriate in sEMG control systems because it produces better classification accuracy and a more constant controller delay and reduces the length of the maximum delay .With large segments, overlapped windowing is necessary in order to avoid long latency in real time operation.

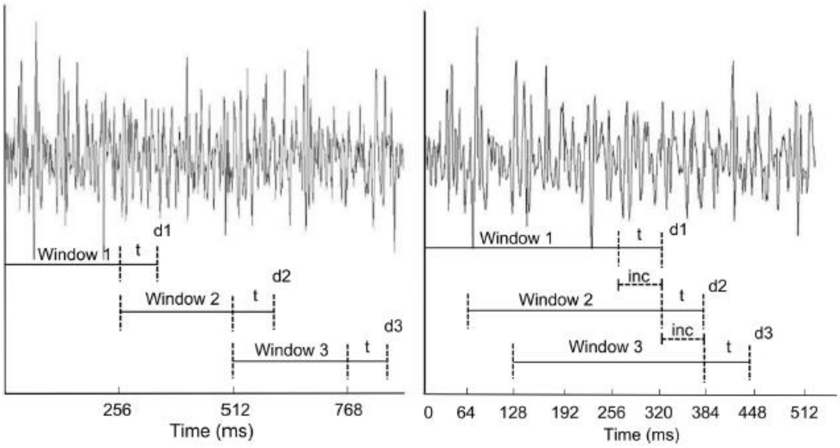


Fig.14. Windowing techniques. adjacent windowing (left). Overlapped windows (right)

1. Overlapped Windows

Englehart and Hudgins explain that the processing time required to analyze the EMG can be much less than the length of the analysis window (*Ta*), causing the processor to lie idle a majority of the time. Fig.15 shows an example of using disjoint windows and visually demonstrates that class decisions (labeled as d1, d2, and d3 in Fig.15 and Fig.16) can be produced relatively infrequently and that the processor is not being used to its full capacity. To use the capabilities of the processor fully, Yamada et al. and Englehart et al. suggested increasing the frequency of class decisions by "sliding" the window along at increments that are slightly larger than τ. In this way, as soon as a class decision is generated, the controller immediately begins processing the next class decision on a "new" window of data. Fig.16 (note the differences in lengths of time in the *x*-axes between Fig.15and Fig.16) shows how the use of overlapped windows increases the frequency of which class decisions are made and nearly maximizes the use of the processor. When the classifier uses overlapped windows, the amount of new data that will be added to each new analysis window (i.e., the amount of "shift") will be defined as *T*new. Theoretically, minimum overlap can be achieved when *T*new = τ. ; However, in practice, *T*new will be slightly larger than τ.

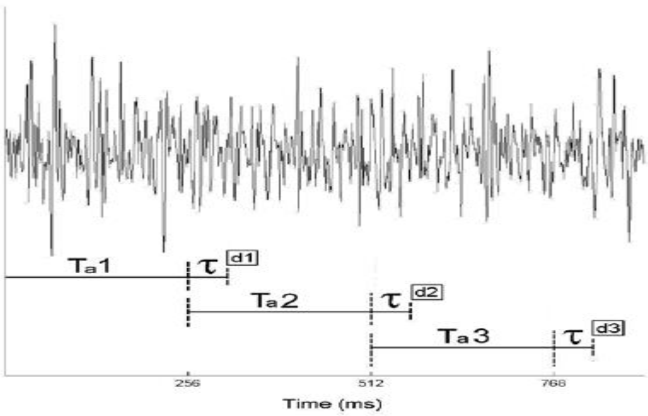


Fig.15.Example of disjoint windowing of single channel of electromyographic data (*Ta* = 256 ms, τ = 64 ms). Each analysis window (*Ta*) takes finite time to process (τ) before a decision (d1, d2, and d3) can be produced. Note that time required to process each window (τ) is much less than analysis window length and therefore processor is lying idle a majority of time. Figure is modified version. *Source:* Englehart K, Hudgins B. A robust, real-time control scheme for multifunction myoelectric control. IEEE Trans Biomed Eng. 2003;50(7):848–54. [PMID:12848352] DOI:10.1109/TBME.2003.813539

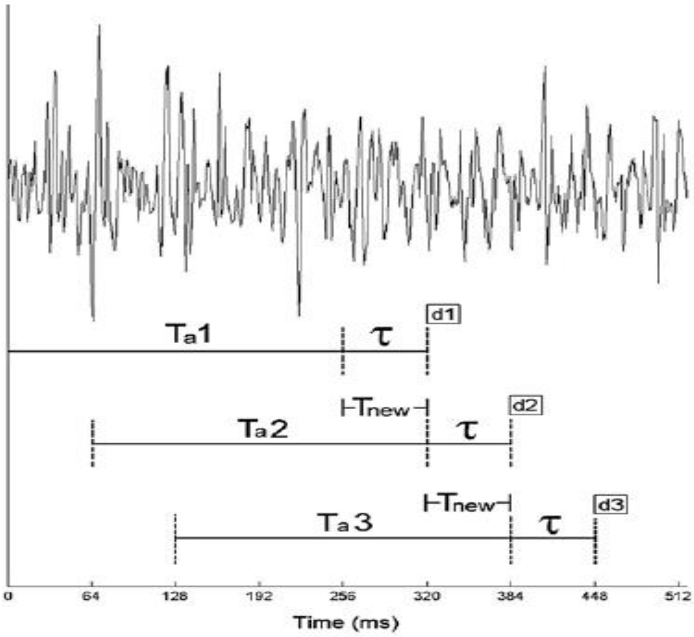
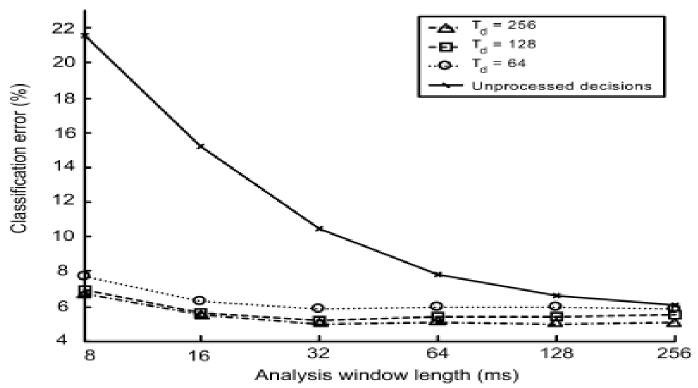
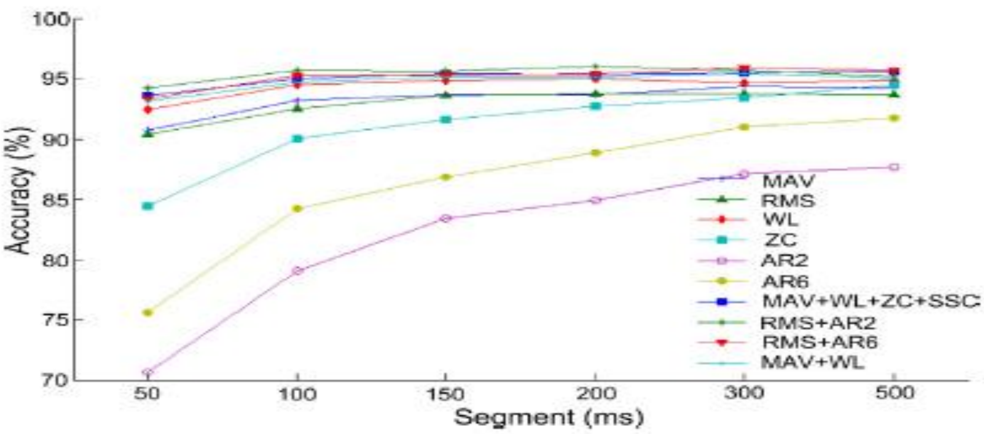


Fig.16. Example of overlapped windowing of single channel of electromyographic data (*Ta* = 256 ms, τ = *T*new = 64 ms). When overlapped windows are used, analysis window slides along at relatively small increments, adding newly collected data and discarding oldest data. In this example, amount of new data in each window (*T*new) is exactly equal to amount of time required to process data from previous analysis window (τ). Setting amount of overlap equal to processing time allows controller to begin processing next class decision immediately when decision on previous window's data has been completed. Overlapped windows increase frequency of class decisions, which makes postprocessing technique of majority voting tractable. Figure is modified version. *Source:* Englehart K, Hudgins B. A robust, real-time control scheme for multifunction myoelectric control. IEEE Trans Biomed Eng. 2003; 50(7):848–54. [PMID: 12848352]DOI:10.1109/TBME.2003.813539

3.1.2. Segment length

Large data windows increase classification accuracy, but the drawback is that more time is required to collect and process larger data sets. Thus, a trade-off has to be done between classification accuracy and real-time constrains. The effect of classification errors and time delay on controllability has mostly been investigated in the context of upper limb prostheses but is essential in all real-time applications. A test where the user moved a virtual limb to one of six predetermined target positions showed that classification errors less than ∼10% yield controllable systems whereas classification errors over ∼35% yield systems that are not control-label. Estimates of the delay (i.e. the time between onsets of user's command and actuation of the device) which does not make the prosthesis feel unresponsiveness to the user range between50 ms and 400 ms. This delay range corresponds to window lengths of 50–400 samples and 25–200 samples for sampling frequencies of 1000 Hz and 500 Hz, respectively. In theory, a segment of $t \leq 200$ ms contains enough information to estimate motion states of a limb because that is the minimum interval between distinct contractions. However, high classification accuracy is also possible with segments less than 200 ms if the features have been selected carefully and if majority voting(MV) is used as a post processing mechanism, MV is a common postprocessing technique that aims to increase the overall classification accuracy by analyzing the current class decision along with then − 1 previous class decisions . As is apparent from Fig. 10, the accuracy of the unprocessed decision stream degrades rapidly by decreasing segment length, but MV effectively prevents degradation with the help of more decisions available with short segments. It should be noticed that MV also increases the delay because the more votes is used the more windows need to be processed before the final decision. No appreciable difference exists in classification accuracy whether a large window with small number of votes or a small window with a large number of votes is used. However, short windows are recommended because they need less storage space. The saving in storage space is important when implementing the classifier as an embedded system where memory is usually scare resource. When MV is used with overlapped segmentation, no great improvement on performance is apparent, but there is a notable decrease in the discrepancy of accuracy over different sessions. The optimal window length also depends on the feature vector calculated from windows in pattern recognition-based classification, as shown in Fig.17





The Fig.18. Classification accuracy for some single features and feature vectors. Over-lapped segmentation with an increment of 200 ms was applied for segment lengths of 300 ms and 500 ms while disjoint segmentation was applied for the other segment sizes. MAV = mean absolute value; RMS = root mean square; WL = waveform length; ZC = zero crossing; AR2 = 2nd order autoregressive coefficients; AR6 = 6thorder autoregressive coefficients.

3.1.3. The effect of segmentation strategies on the delay

Farrel presented equations to estimate the worst, aver-age and best case delays as well as delay ranges in the context of different segmentation strategies. These equations are presented in Table1. The equations assume the transition between the con-traction classes to be instantaneous but have still shown to produce accurate estimates of the controller delay. The delay is a function of the window length, processing time, amount of window overlap, and the number of majority votes used. The window shift Tnew is related to processing time τ. which is determined by the analysis window length Ta, processor, memory, type of features, algorithms used to extract features and perform pattern recognition, and the number of sEMG channels. Thus, the only parameters under the designer’s direct control for a given feature set are the window length and the number of majority votes.

Classifier type	Worst-case delay	Average delay	Best-case delay	Difference between best and worst case
No overlap, no majority voting	$D=\frac{1}{3}T_a+\tau$	$D=T_a+\tau$	$D=\frac{1}{2}T_a+\tau$	T_a
No overlap, with majority voting	$D=\left(\frac{n}{2}+1\right)T_a+\tau$	$D=\left(\frac{n+1}{2}\right)T_a+\tau$	$D=\left(\frac{n}{2}\right)T_a+\tau$	T_a
Overlap, no majority voting	$D=\frac{1}{2}T_a+T_{new}+\tau$	$D=\frac{1}{2}T_a+\frac{n}{2}T_{new}+\tau$	$D=\frac{1}{2}T_a+\tau$	T_{new}
Overlap, with majority voting	$D=\frac{1}{2}T_a+\left(\frac{n+1}{2}\right)T_{new}+\tau$	$D=\frac{1}{2}T_a+\left(\frac{n}{2}\right)T_{new}+\tau$	$D=\frac{1}{2}T_a+\left(\frac{n+1}{2}\right)T_{new}+\tau$	T_{new}

3.2. Feature Extraction

Raw sEMG signals are mapped into smaller-dimension feature vectors because features describe the information content of the signal more efficiently than random and complex raw signal. Because of the smaller size of the feature vectors, classifiers also perform faster, which improves the real-time properties of the system. EMG features can be grouped into four categories according to the domain where they are calculated:

1) Time domain (TD) features,

2) Frequency or spectral domain (FD) features,

3) time-scale or time-frequency domain (TFD) features

Table 2 shows some features of each category. SD features can be calculated only from HD-sEMG configurations. A more detailed description of features especially that of TD and FD features can be found in Refs.Feature selection is the most important step in sEMG signal processing because the effect of the feature set on classification accuracy is even greater than the effect of the type of the classifier. Three properties determine the quality of the feature space: maximum class separability, robustness, and computational complexity. A high quality feature space results in clusters with maximum class separability or a minimum overlap, thus minimizing the misclassification rate. Robustness describes the ability of the feature space to preserve cluster separability in a noisy environment. The computational complexity of the feature set should be low so that the related procedure can be implemented with reasonable hardware and in real-time. Although several studies have been made to find optimal features for classification of sEMG signals, few of these studies have made deeply quantitative comparisons of their qualities, particularly from the viewpoint of redundancy. In addition, there is little consensus between these studies because of significant differences in the study details: most notably, the number of postures classified, posture types and durations, data acquisition and the classification system used, the number of subjects and the dataset sizes. Comparative studies have shown that TD features achieve higher accuracy for the LDA classifier, whereas TFD features out-performed them for the SVM classifier. considering the robustness of LDA over SVM, TD features classified with LDA have been suggested as optimal for sEMG classification. However, this conclusion bases on studies made in low-noise laboratory conditions, and more study is needed to find the features capable to maintain high classification accuracy in real use. The classification system has also been shown to be subject dependent, and therefore it may be beneficial to tailor a classification system to each subject. The following subsections describe the feasibility of each feature group in sEMG classification in more detail.

3.2.1. Time domain (TD) features

TD features are the most commonly used feature group in sEMG signal classification. Their major advantage is that they are fast to calculate because no mathematical transformation is needed. However, because TD features are based on signal amplitude, they are relatively sensitive to noise and artifacts. Based on observations of scatter plots and mathematical properties, Phinyomark et al. divided TD features into four main types:

(1) Energy and complexity information methods.

(2) Frequency information methods.

(3) Prediction model methods.

(4) Time-dependence methods.

Adding the features from the same category in the feature vector may increase the performance only slightly, due to small difference in feature space. Some features from each group are presented in Table 2.There have been attempts to determine an optimal TD feature vector for several classifiers. Examples of TD feature vectors used in sEMG studies are presented in Table 3. The most common combination is the LDA classifier with Hudgin's feature vector consisting of mean absolute value (MAV), waveform length (WL), zero crossing (ZC), and signal slope changes (SSC). MAV estimates an average of absolute value of the EMG signal amplitude and WL, the cumulative length of the waveform over the time segment. WL is a combined measure of signal amplitude, frequency and duration describing signal complexity. ZC is a number of times that amplitude values of the EMG signal cross zero amplitude level and SSC the number of times that slope of the EMG signal changes sign. The benefits of Hudgin's feature set are relatively high classification accuracy, stability against changes in segment length, low discrepancy over several sessions, and computational simplicity. In addition to LDA, it has also been shown to be an optimal TD feature vector at least for SVM and multilayer perception (MLP).It is also common to combine autoregressive (AR) coefficients with Hudgin's features (often referred to as the TDAR feature vector). This feature vector has shown high classification accuracy with LDA MLP and Gaussian mixture models (GMM). Autoregressive (AR) and Cepstral (CC) coefficients are two prediction model features used in sEMG signal classification for which AR coefficients are more commonly applied. AR and CC coefficients are computationally more complex than other TD features and need longer segments. The larger the model order, the greater the computation time needed to determine the coefficients. Thus, the model should be kept as simple as possible without sacrificing classification accuracy. Previous studies have suggested 3rd , 4^{th} and 6^{th} AR order model as an optimal model for classification of movements from sEMG signals. The probability density function of sEMG amplitude has also shown promise as a TD feature permitting sEMG classification [140]. In a simulation study that classified sEMG data according to three force levels the core shape model outperformed higher order statistic combinations in all simulations due to the precise PDF shape screening embedded in its formalism.

Table 2

	Mathematical definition
Time domain features	
Energy and complexity information methods	
Mean absolute value	$MAV = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert$
Integrated EMG	$IEMG = \sum_{i=1}^{N}\lvert x_i\rvert$
Variance	$VAR = \frac{1}{N-1}\sum_{i=1}^{N}x_i^2$
Root mean square	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}$
Waveform length	$WL = \sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert$
Log detector	$LOGDET = e^{1/N\sum_{i=1}^{N}\log(\lvert x_i\rvert)}$
Frequency information methods	
Zero crossing	
Wilson amplitude	$WAMP = \sum_{i=1}^{N-1}[f(\lvert x_n - x_{n+1}\rvert)]$
Slope sign change	$SSC = \sum_{i=2}^{N-1}[f(\lvert(x_i - x_{i-1})\times(x_i - x_{i+1})\rvert)]$ where $f(x) = \begin{cases} 1, & \text{if } x \geq \text{throshold} \\ 0, & \text{otherwise} \end{cases}$
Prediction model methods	
Autoregressive coefficients	$x_n = \sum_{i=1}^{P}a_{i,n}x_{n-i}$, P - model order, $a_{i,n}$ - ith AR coefficient at time instant n
Cepstral coefficients	$c_n = -a_n - \sum_{k=1}^{n}\left(1-\frac{k}{n}\right)a_k c_{n-k}$, $c_1 = -a_1$, c_n - nth cepstrum coefficient, a_i - AR coefficient
Time-dependence methods	
Mean absolute value slope	$MAVS_i = MAV_{i+1} - MAV_i$; $i = 1,\ldots,K-1$; K - number of segments covering the signal
Histogram of EMG	HEMG divides elements in the EMG signal into equally spaced segments and returns number of signal elements for each segment.
Frequency domain features	
Mean frequency	$MNF = \sum_{j=1}^{M}f_jP_j / \sum_{j=1}^{M}P_j$
Median frequency	$\sum_{j=1}^{MDF}P_j = \sum_{j=MDF}^{M}P_j = \frac{1}{2}\sum_{j=1}^{M}P_j$
Modified mean frequency	$MMNF = \sum_{j=1}^{M}f_jA_j / \sum_{j=1}^{M}f_jA_j$
Time-frequency domain features	
Short time Fourier transform	$STFT(k,m) = \sum_{r=1}^{N-1}x(r)g(r-k)e^{-j2\pi mi/N}$; g - window function; k - time sample; m - frequency bins
Continuous wavelet transform	$WT_x(\tau,a) = \frac{1}{\sqrt{a}}\int x(t)\Psi\left(\frac{t-\tau}{a}\right)dt$; t - translation parameter; a - scale parameter; Ψ - mother wavelet function
Discrete wavelet transform	DWT splits the signal into an approximation and detail coefficients by passing it through complementary low- and high-pass filters. The approximation coefficients are further split into a second-level approximation and detail coefficients. By repeating the process, one signal is broken down into many lower resolution components.
Stationary wavelet transform	SWT does not decimate the signal at each stage, avoiding the problem of nonlinear distortion of the DWT and WPT.
Wavelet packet transform	WPT is a generalized version of DWT that is applied to both low-pass results (approximations) and high-pass results (details).

Table 3

Feature vector	Classifier	Classification accuracy (%)	Classes	Bipolar electrodes	Subjects
MAV, WL, ZC, SSC	SVM	96	6	4	11H
MAV, WL, ZC, SSC, AR6	LDA	97	10	3	12H
MAV, WL, ZC, SSC, AR6, RMS	GMM	97	6	4	12H
MAV, WAMP, VAR, WL	ANN	98	12	32	1H
MAV, WAMP, AR, CC	LDA	70[1], 78[2], 87[3]	4	2	8H
MAV, WL, AR, CC	LDA	70[1], 78[2], 88[3]	4	2	8H
WL, LOGDET, AR, CC	LDA	70[1], 78[2], 88[3]	4	2	8H
SE, CC, RMS, WL	LDA	98	11	4	4H
IEMG, WL, VAR, ZC, SSC, WAMP	GRA	96	11	7	12H
AR6, MAV	LDA	98H, 79A	11	4	5H, 5A
AR6, ZC	LDA	97H, 75A	11	4	5H, 5A
AR6, SSC	LDA	97H, 74A	11	4	5H, 5A
AR6, WL	LDA	98H, 79A	11	4	5H, 5A
AR6, RMS	SVM	96	6	4	11H
AR, HIST	CKLM	93A, 97H	8	3	2A, 1H

3.2.2. Frequency domain features

Frequency domain (FD) features can be used to estimate muscle fatigue, force production and changes in motor unit recruitment and firing patterns. FD features are calculated from power spectral density (PSD), which can be estimated using Periodgram or parametric methods. PDS is mainly determined by the firing rate of the recruited motor units in the low-frequency range (below 40 Hz), whereas the morphology of their MUAPs traveling along the respective muscle fibers mainly determines the high-frequency range (above 40 Hz).Phinyomark et al. studied the properties of thirty-seven TD and FD features and found that TD features were superior to FD features. In addition to their poorer classification accuracy, FD features are computationally more complex than TD features. However, combining FD features with successful TD features may yield more robust classification than a feature vector consisting solely of TD features. Phinyomark et al. suggested mean frequency (MNF) as a potential candidate to combine with TD features because its discriminant pattern in the feature space is different from that of TD features. Phinyomark et al. [121] modified the MNF and median frequency (MDF) features in order to increase the robustness property of these features by applying mean and median to the amplitude spectrum instead of the power spectrum because the variation of the amplitude spectrum is smaller. They compared the tolerance of sixteen traditional TD and FD features, and modified MNF and MDF features against white Gaussian noise. The results showed that a modified MNF is the most robust feature regarding white Gaussian noise. Therefore, modified MNF was suggested as a highly potential feature to augment the other features for a more powerful and robust feature vector. Recently, two novel FD features derived from discrete Fourier transform and muscle coordination has shown robustness against variations in contraction force.

3.2.3. Time-frequency domain

Features Time-frequency domain (TFD) features used in sEMG classification include short time Fourier transform (STFT), continuous Wavelet transform (CWT), discrete wavelet transform (DWT), wavelet packet transform (WPT) and stationary wavelet transform (SWT). The drawback of STFT is that it cannot increase both time and frequency resolution simultaneously .CWT, DWT and SWT overcome this deficiency by providing good frequency resolution with poor time resolution in low frequency band but poor frequency resolution with good time resolution in high frequency band. Since DWT is computationally more efficient than CWT, it has become the most common TFD feature in sEMG interfaces. WPT has also gained interest because of its ability to provide the frequency information in both low frequency band and high frequency band. Although TFD features are computationally more complex than TD features, they can be implemented with fast algorithms that have shown to be capable to meet the real-time requirements in sEMG classification when appropriate dimensional reduction and segmentation technique are used. Wavelet transforms may improve the robustness of the system compared to TD and FD features because by using subsets of wavelet coefficients the analysis can be restricted only to interesting frequency bands.TFD features yield a high-dimensional feature vector that requires dimensionality reduction transformation to increase the speed and accuracy of the classification. The most popular feature projection algorithms in sEMG signal classification are the principal component analysis (PCA) and uncorrelated LDA (ULDA). However, the feature extraction applied for wavelet coefficient is usually a TD technique. TD features can be calculated either directly from the wavelet coefficients or the reconstructed sEMG signal. Most studies of sEMG analysis have concluded the Daubechies wavelet family to be one of the most suitable for sEMG signal analysis. Phinyomark et al. Compared several TD and FD features computed of the sEMG signal reconstructed using DWT coefficients of different levels. Useful feature vectors included a feature vector consisting of ZC, WAMP, and MAV computed of the second-level reconstructed sEMG signal with the Db7 wavelet and the Myopulse percentage rate (MYOP) feature of the first-level reconstructed sEMG signal with the Db8 wavelet. Phinyomark et al. have also suggested DWT as an optimal method to remove white Gaussian noise (WGN) from sEMG signals. Conventional filters cannot effectively remove WGN because its frequency components fall in the energy band of the physiological sEMG signal.

3.3. Dimensionality reduction

Dimensionality reduction, also called phenomenological analysis, aims to improve signal classification, reducing the dimensions of the feature vector by removing redundant information without disrupting the relevant data. According to, and there are two main strategies: feature subset selection (or just feature selection) and feature projection.

3.3.1. Feature projection

Feature projection creates a new and smaller feature set by identifying the optimal combination of the original features. The simplest method employs a linear transformation matrix to map the original features into the reduced-dimension space. The most popular linear mapping functions are Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).

3.3.1.1. **Principal Component Analysis (PCA)**

PCA, which is also known as Karhunen-Loéve transform or Singular Value Decomposition, creates an uncorrelated reduced-dimension set of variables from the original ones. To achieve this, the linear transformation matrix is calculated by searching for the directions with higher variations. This implies the consideration of those features that provide more variation, so low-order principal components are kept while the higher-order ones are discarded. Thus, the main limitation of this method is the preliminary assumption that maximum variance directions provide maximum discrimination, as no class information like between-class or within-class scatter is taken into account. In addition, PCA is scale-sensitive and some principal components might be obscured by elements with higher variances.

Englehart *et al.* [9] compared feature projection using PCA, and Euclidean distance class separability (CS) as FSS. The tested features were Hudgins' time domain features (TD): MAV, MAVS, ZC, SSC and WL; and time-frequency domain features: STFT, WT and WPT. After reducing the dimensions of the previous feature sets, classification performance was evaluated by LDA classifier and Multi-Layer Perceptron (MLP) classifier. Results show that for dimensionality reduction PCA is more effective than CS, especially for time-frequency domain features.

3.3.1.2. Linear Discriminant Analysis (LDA)

LDA mapping is based on a classification criterion that maximizes the ratio of between-class and within-class variance. As previously seen, LDA can be used as a wrapper objective function (FSS) or as a classifier itself, however in this subsection, the focus will be its application in dimensionality reduction.

According to Wang LDA is a twofold process that first defines the discriminant functions and then solves the criterion function. Discriminant functions are a series of input-output functions generated by the classifier, which relate the input features to the parameter set of the class. In dimensionality reduction, this is a prior estimation of the feasible reduced features, calculated from a training data set. In the second step, these discriminant functions are introduced into the criterion function that is based on between-class and within-class covariance. Depending on the decision rule implied in the criterion function, the optimal solution will minimize (Generalized LDA) or maximize (Fisher's linear discriminants) the function.

3.3.2. Feature selection

Feature Subset Selection (FSS) seeks for the optimal subset, with highest classification rate, among all existing features. This approach requires a search strategy to select candidate subsets, and an objective function that test them and provide feedback to new candidate selection. Depending on the evaluation process, objective functions can be classified into filters and wrappers. The former assess the candidate subset based on their information content (interclass distance, statistical dependence or information-theoretic measures); whereas the latest are classifiers that evaluate the candidates according to their classification accuracy.

Oskoei and Hu developed a complex algorithm based on FSS. For this study, the selected search strategy was Genetic Algorithm that simulates "survival of the fittest" evolutionary process. Both classes of objective functions were analyzed in the research: Davies Boulding index and Fisher Linear Discriminant Analysis (represent clusters' dispersion comparing to their scatter) as filters, and Linear Discriminant Analysis (LDA) as wrapper. LDA employs a discriminant function to divide the feature space into different labeled subspaces by the hyperplane decision surface, using a training data set. More details about LDA are provided in the next subsection. Time domain (MAV, MAVS, RMS, VAR, WL, ZC, SSC and WAMP) and frequency domain features (AR, FMN, FMD and FR) were analyzed by FSS and then classified by an Artificial Neural Network. WL showed the highest discriminating information for classification, followed by MAV and RMS, and AR in the third place. However, all this process requires complex calculations that increase the computation time. This approach was therefore presented, as a pre-offline training of the classifier to upgrade its performance.

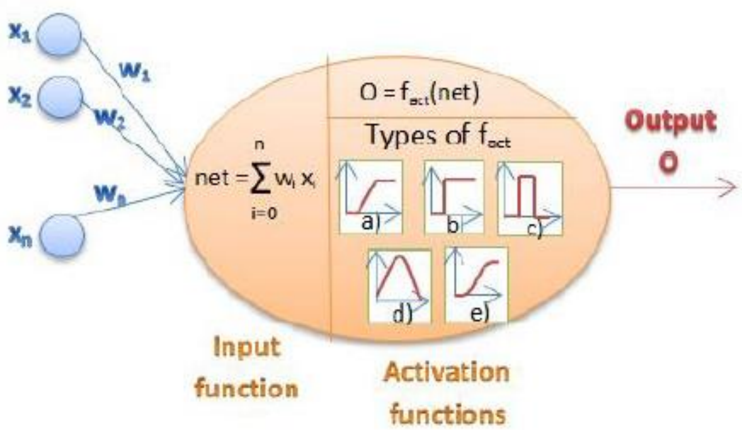
CHAPTER 4

4. Classification

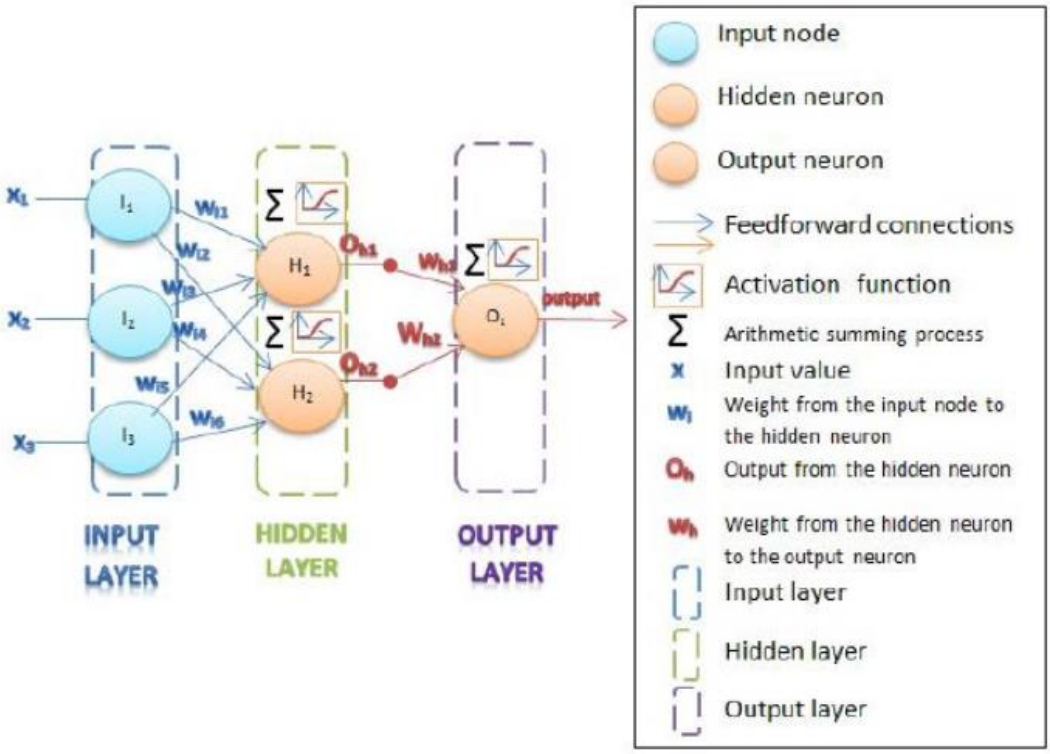
Once the features have been extracted from the raw signal (feature extraction) and the features with redundant infor- mation have been reduced (dimensionality reduction), some classifiers should be deployed to distinguish different cate- gories among the reduced feature vector. Then, these obtained categories are going to be used in the next stage as control commands, i.e. the controller. As can be seen in Figure 4, several techniques are deployed to classify data, e.g., neural networks (NN), Bayesian classifier (BC), fuzzy logic (FL), linear discriminant analysis (LDA), support vector machines (SVM), hidden Markov models (HMM) and K- nearest neighbor (KNN). Nevertheless, before classifying EMG and EEG signals, it is important to bear in mind that these signals are expected to present variations in the value of a particular feature. Oskoei and Hu, explain that there are external factors, such as changes in electrode position, fatigue, and sweat that cause changes in a signal pattern over time. Besides, according to, a classifier should meet the following requirements to categorize EMG and EEG signals properly: (i) it should be able to cope with varying patterns optimally; (ii) it should prevent over fitting; and (iii) it should be adequately fast, in order to meet real-time constraints.

4.1. Neural Networks (NN)

Neural Networks (NN) are inspired in neurons' ability to collect process and disseminate action potentials. NN are composed of artificial neurons, information-processing units of a set of inputs and weights.
In the first step of artificial neuron processing, the net is calculated by the arithmetic sum of the inputs and weights, as depicted in Fig.19, where n is the total number of input units, xi is the input of one unit and wi, its associated weight. The next step evaluates the obtained net with an activation function (fact). This function works as a logic gate that is activated (output value near +1) or inactivated (output value near 0) depending on the input net value. This activation must be nonlinear being the proposed activation functions: threshold linear, step, arbitrary step, exponential or sigmoid.



The most common NN is the Multilayer Perceptron (MLP) formed by several input units, several hidden layers (usually one or two) and a level of output units, as represented in Fig.20. Each input unit is connected to each unit in the hidden layer with an associated weight. Similarly, that hidden layer is connected to the artificial neurons of the following hidden or output layer. This layout corresponds to a fully connected network, but there are also partially connected networks.

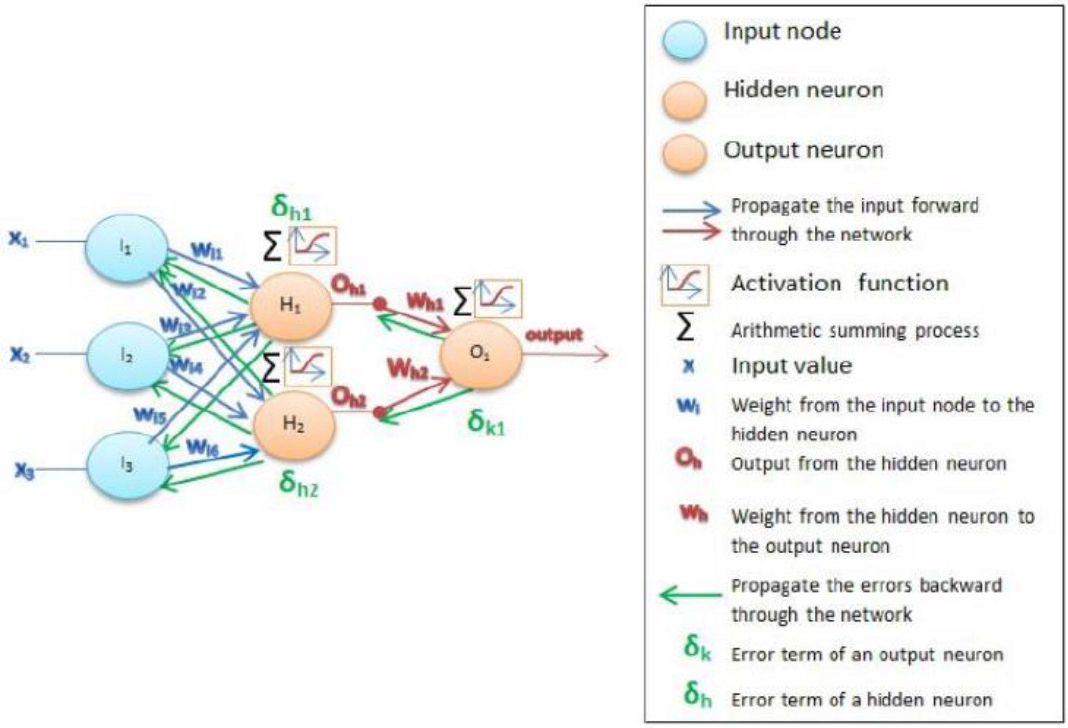


The advantages of NN are based on artificial intelligence learning skills, being able to:

- Learn both linear and non-linear relationships directly from the input data without an a priori mathematical model.
- Adapt to changing conditions.
- Process corrupted or partial data sets.

Nevertheless, its learning performance is biased by the provided number of examples. This workflow implies a training step to adjust network weights. This introduces the concept of back-propagation neural networks (BPNN) in which each unit or neuron receives feedback from the following layer to adapt their weights and improve the classification performance; see Fig.21. Units might even have self-connections. This recurrence supplies information about past events working as a short-term memory.

Ahsan et al. proposed an optimized design of artificial NN to classify four predefine hand motions (left, right, up and down) using a back-propagation algorithm. The foremost BPNN employed 7 inputs, 10 neurons in the hidden layer and 4 outputs along with a back propagation training algorithm called Levenberg-Marquardt (LM) that is used to solve non-linear least squares problems. To evaluate NN classification performance 70% of the input data was employed for training, 15% for validation and 15% for testing. The designed NN strcture obtained an average classification rate during training of 88.4%



There are two main learning paradigms: supervised or unsupervised learning. In supervised learning, the user provides a series of input-output examples that the BPNN uses to compare the output signal to the desired or target output. Therefore, this approach propagates the input forward through the network, calculates the error of each step until a termination condition is satisfied and finally propagates the calculated errors backward to optimize the model. On the other hand, in unsupervised learning, there is no target output so the NN must extract statistical information from the input and develop new classes automatically.

Subasi et al. designed a Wavelet Neural Network (WNN) to classify neuromuscular disorders based on EMG signals. AR coefficients were calculated from the input data representing the target classes: normal, myopathic and neurogenic disorder. The proposed WNN design was built by a mono-hidden-layer forward neural network whose node activation function was based on dyadic discrete Morlet wavelet basic function. In order to test the implemented WNN classification performance, it was compared with a BPNN composed by an AR input layer, a fifty-neuron hidden layer and a three-neuron output layer. Results showed a success rate of 90.7% for WNN and 88% for BPNN.

Chu et al. presented a real-time EMG pattern recognition system based on linear-nonlinear feature projection for a multifunction myolectric hand, using MLP classification. Nine hand motions were recorded with a four channel EMG from the forearm. The proposed method processed the data by extracting WPT features, reduced feature dimensions with PCA and applied Self-Organizing Feature Map (SOFM) to transform the PCA-reduced feature set into a new feature space with higher class separability. Finally data was classified with a MLP composed of: a) an input layer built from the eight outputs of the SOFM for the four EMG channels, b) two nine-neuron hidden layers and b) a nine-neuron output layer. Experimental results proved the suitability of this technique for real-time applications with an overall processing time (including virtual hand control) of 125ms. The obtained MLP average classification success rates were 95.795% when only PCA was applied, 97.024% for PCA+SOFM combination and 97.785% for SOFM algorithm alone.

4.2. Bayesian Classifiers ((BC)

Bayesian Classifiers (BC) is a standard statistical classification method that applies Bayes' to sort input data based on a given hypothesis. Therefore, training data creates a probabilistic model to classify each input with a probability associated for each feasible class:

$$P(c|D)=P(D|c)P(c)P(D)$$

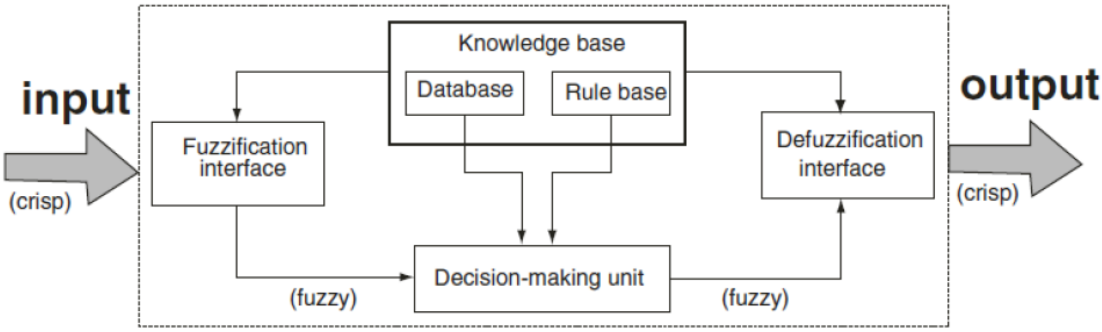
where P(c) is the prior probability that the input data corresponds to that class, P(D) is the prior probability that the training data D will be observed (independently of the class hypothesis that is being analyzed), and P(D|c) is the probability of observing data D assuming that the hypothesis that D belongs to class c, holds. P(c|D) is the posterior probability or confidence classification level that relates input D to class c. Bu et al proposed a Bayesian Network (BN) for motion prediction using EMG signals. The presented model comprised BC to forecast motions, in parallel with a probabilistic NN called Log-Linearized Gaussian Mixture Network (LLGMN) to calculate the probability density functions of the input signals. In BC, motion prediction hypothesis was based on hand position and previous motion. The final command was determined combining both BC and LLGMN outputs. To demonstrate the feasibility of this technique, upper limb motions were analyzed during a cooking task yielding in classification rates of 85.1% for LLGMN alone, and 92.9% for the proposed BN.

4.3.Fuzzy logic

Fuzzy logic presents several advantages in bio-signal processing as it is able to handle uncertain, imprecise and even contradictory data; detect complex hidden patterns and allow experience and empirical information integration in the system to improve classification performance. Fuzzy inference systems (FIS) are excellent simulators of human decision-making process.

As explained by Sivanandam et al. fuzzy logic works with fuzzy sets or series of linguistic variables that model problems' uncertainty (i.e. qualitatively: low, medium, high; quantitatively: few, several, many; etc.). Therefore numerical inputs must be transformed into these fuzzy values by a membership function, whose values range from the continuous interval following a trapezoidal, triangular or Gaussian waveform. This process is called fuzzification. Once in the fuzzy domain, classification is performed according to a predefined set of IF THEN fuzzy rules. The output of this step is another fuzzy variable that needs to be converted into a crisp (not fuzzy) quantity again by defuzzification.

Thus FIS comprises fuzzification interface, membership functions database, fuzzy rules base, decision-making unit and a defuzzification interface. See Fig.22.



Ajiboye and Weir designed a pattern recognition algorithm based on heuristic fuzzy logic for multifunctional prosthesis EMG control. The multiinput-single-output fuzzy system included:

1) Input membership functions based on the mean and standard deviation of the signal to fuzzify the input into OFF, LOW, MED and HIGH;

2) an inference rule base to classify the data by processing the linguistic inputs.

3) a membership function to defuzzify the inference rule base linguistic outputs. In addition, a fuzzy c-mean clustering method was employed for data reduction, and inference rule base generation so that clustering performance was optimized. The obtained overall classification rates ranged from 94% to 99%.

4.4 .Linear Discriminant Analysis(LDA)

As it has been previously explained, Linear Discriminant Analysis (LDA) is an algorithm able to reduce feature dimensions and classify them. Xiong and Cherkassky reported that LDA's primary attractiveness is its ability to interpret "global" characteristics of the data to predict the decision boundary. LDA classification searches for linear combinations that maximize the distance between classes while minimizing the within-class variance. Hence, LDA does not employ any predefined assumption of the class distributions, rather estimates them from the data.

Balakrishnama and Ganapathiraju described two mapping transformations: Class-dependent transformation that maximizes the ratio of between-class variance to within-class variance; and class-independent transformation which maximizes the ratio of the overall variance to within-class variance.

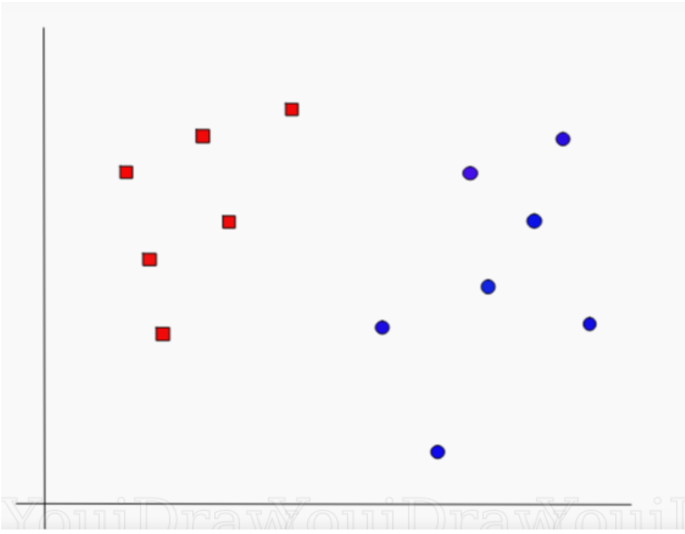
Phinyomark et al. studied the behavior of fifty time-domain and frequency-domain features to improve myoelectric pattern recognition robustness for ten upper limb motions. Feature classification was performed with LDA, obtaining 93.37% average classification accuracy with sample entropy, and reaching 98.87% when increasing the number of features including sample entropy, fourth order cepstrum coefficients, RMS and WL.

4.5. Support vector machine(SVM)

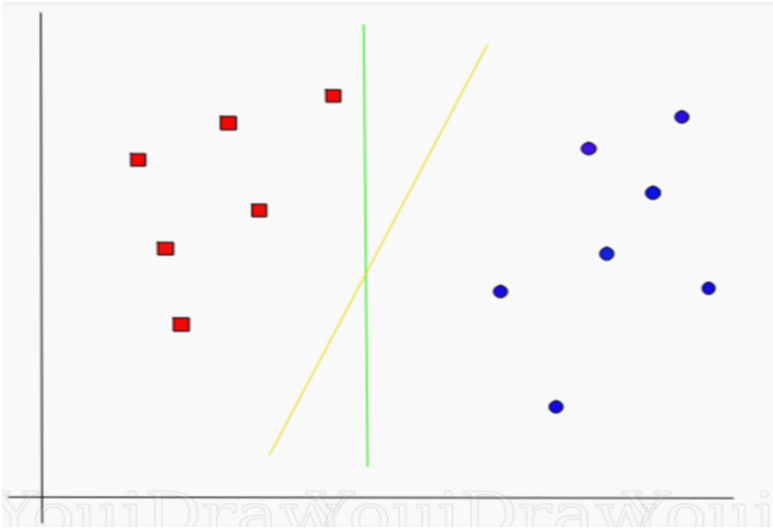
Machine learning involves predicting and classifying data and to do so we employ various machine learning algorithms according to the dataset. SVM or Support Vector Machine is a linear model for classification and regression problems. It can solve linear and non-linear problems and work well for many practical problems. The idea of SVM is simple: The algorithm creates a line or a hyper plane which separates the data into classes.

THEORY

At first approximation what SVMs do is to find a separating line (or hyper plane) between data of two classes. SVM is an algorithm that takes the data as an input and outputs a line that separates those classes if possible. Let's begin with a problem. Suppose you have a dataset as shown below and you need to classify the red rectangles from the blue ellipses (let's say positives from the negatives). So your task is to find an ideal line that separates this dataset in two classes (say red and blue) Fig.23.



Find an ideal line/ hyper plane that separate this dataset into red and blue categories not a big task, right? But, as you notice there isn't a unique line that does the job. In fact, we have infinite lines that can separate these two classes. So how does SVM find the ideal one??? Let's take some probable candidates and Fig.24 it out ourselves.

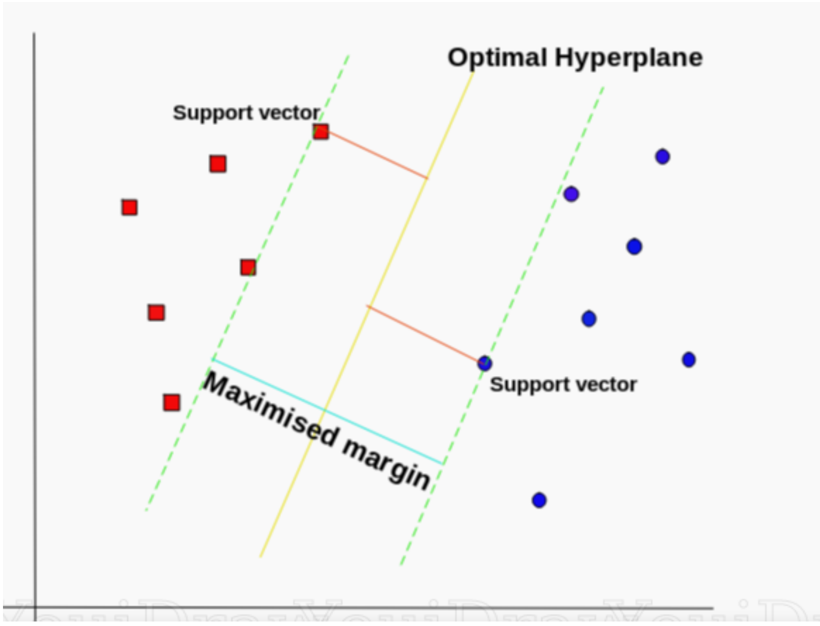


We have two candidates here, the green colored line and the yellow colored line. Which line according to you best separates the data? If you selected the yellow line then congrats, because that's the line we are looking for. It’s visually quite intuitive in this case that the yellow line classifies better. But, we need something concrete to fix our line.

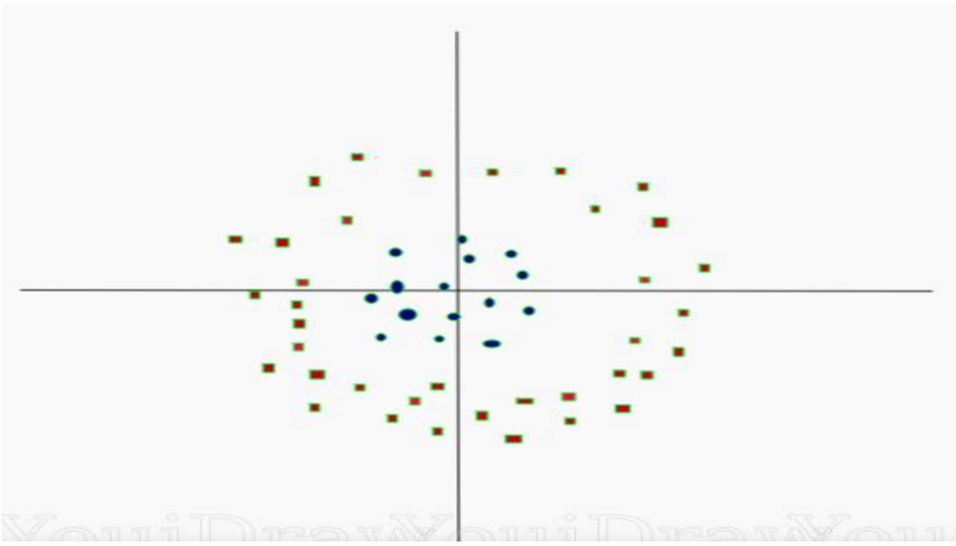
The green line in the image above is quite close to the red class. Though it classifies the current datasets it is not a generalized line and in machine learning our goal is to get a more generalized separator.

SVM’s way to find the best line

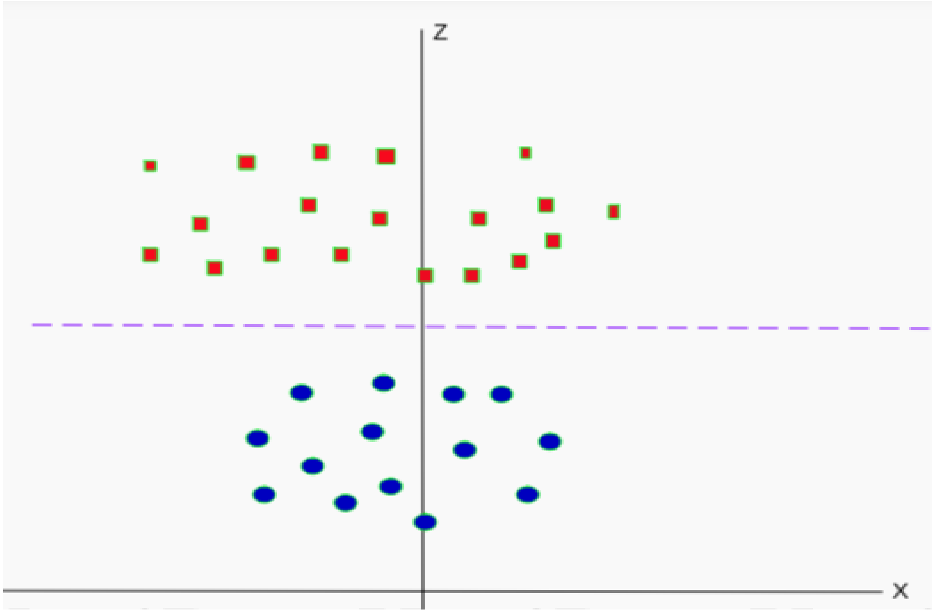
According to the SVM algorithm we find the points closest to the line from both the classes. These points are called support vectors. Now, we compute the distance between the line and the support vectors. This distance is called the margin. Our goal is to maximize the margin. The hyper plane for which the margin is maximum is the optimal hyper plane Fig.25.



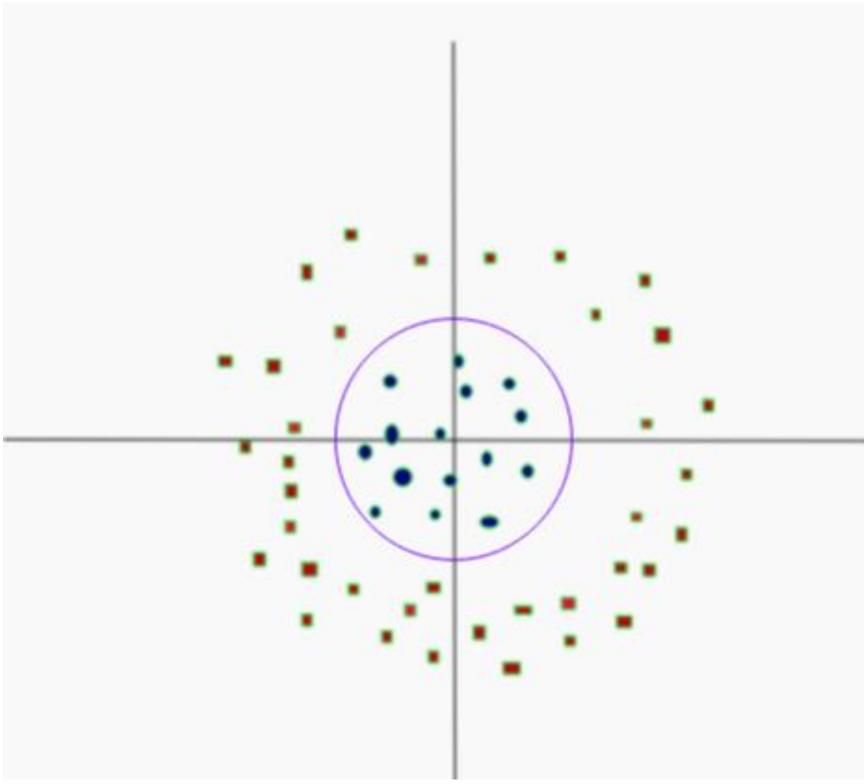
Thus SVM tries to make a decision boundary in such a way that the separation between the two classes(that street) is as wide as possible.Simple, ain't it? Let's consider a bit complex dataset, which is not linearly separable Fig.26.



This data is clearly not linearly separable. We cannot draw a straight line that can classify this data. But, this data can be converted to linearly separable data in higher dimension. Let's add one more dimension and call it z-axis. Let the co-ordinates on z-axis be governed by the constraint, $z = x^2+y^2$ so, basically z co-ordinate is the square of distance of the point from origin. Let's plot the data on z-axis Fig.26.



Now the data is clearly linearly separable. Let the purple line separating the data in higher dimension be z=k, where k is a constant. Since, $z=x^2+y^2$ we get $x^2 + y^2 = k$; which is an equation of a circle. So, we can project this linear separator in higher dimension back in original dimensions using this transformation Fig.28.

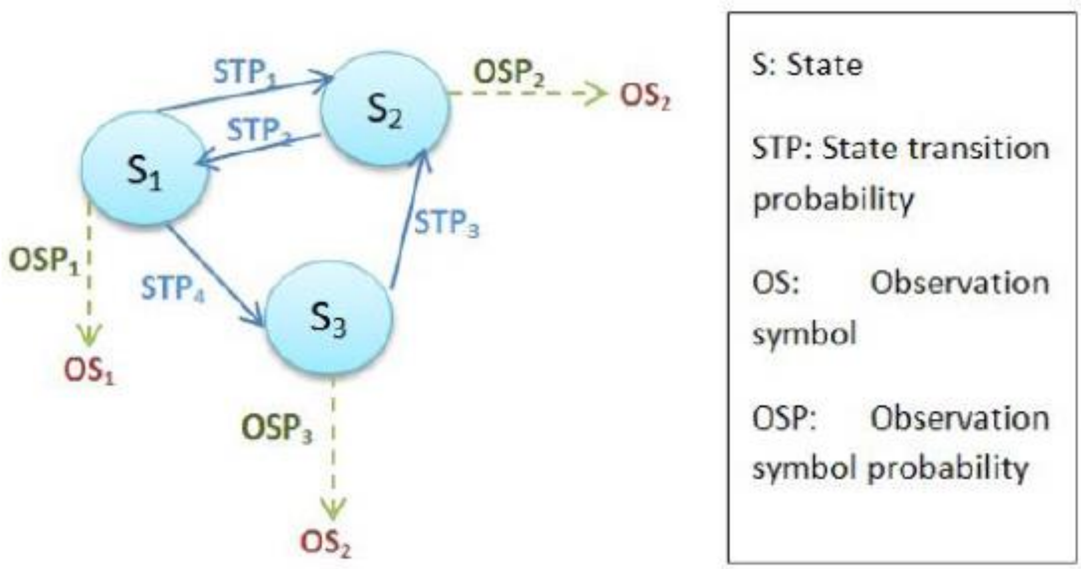


Thus we can classify data by adding an extra dimension to it so that it becomes linearly separable and then projecting the decision boundary back to original dimensions using mathematical transformation. But finding the correct transformation for any given dataset isn't that easy. Thankfully, we can use kernels in sklearn's SVM implementation to do this job**.** Now that we understand the SVM logic lets formally define the hyperplane .

A hyperplane in an n-dimensional Euclidean space is a flat, n-1 dimensional subset of that space that divides the space into two disconnected parts. For example let's assume a line to be our one dimensional Euclidean space(i.e. let's say our datasets lie on a line). Now pick a point on the line, this point divides the line into two parts. The line has 1 dimension, while the point has 0 dimensions. So a point is a hyperplane of the line.

4.6. Hidden markov model (HMM)

Hidden Markov Model (HMM) is a probability-based classifier. It is formed by a network of states related to each other by state transition probabilities. Each state is associated with a probability density function (modelled as a Gaussian mixture) that depicts the observed data probabilistic behavior (Observation symbol probability). HMM's outputs account for the probability of each state, being the highest one the final class or pattern. Usually, the initial-state occupancy probability and state transition matrix are predefined for each model. Therefore training goal is to model the Gaussian probability density function of each state via mean vector and covariance matrix calculation Fig.29.



HMM benefits include the detection of time-varying signal characteristics, ability to model signal dynamics statically, high classification accuracy and low computational cost, suitable for real-time applications.
Chan and Englehart applied HMM to classify six upper limb motions acquired by four EMG channels placed at the wrist, forearm and elbow. The proposed HMM was a state-driven method in which every motion pattern was associated to a state in the model. State transition probabilities were optimize empirically; assuming uniform distribution of the initial state and state-switching probabilities, and fixing a high probability to remain in a given state. The EMG signal classification of the fully connected HMM reached an average accuracy of 94.63%.

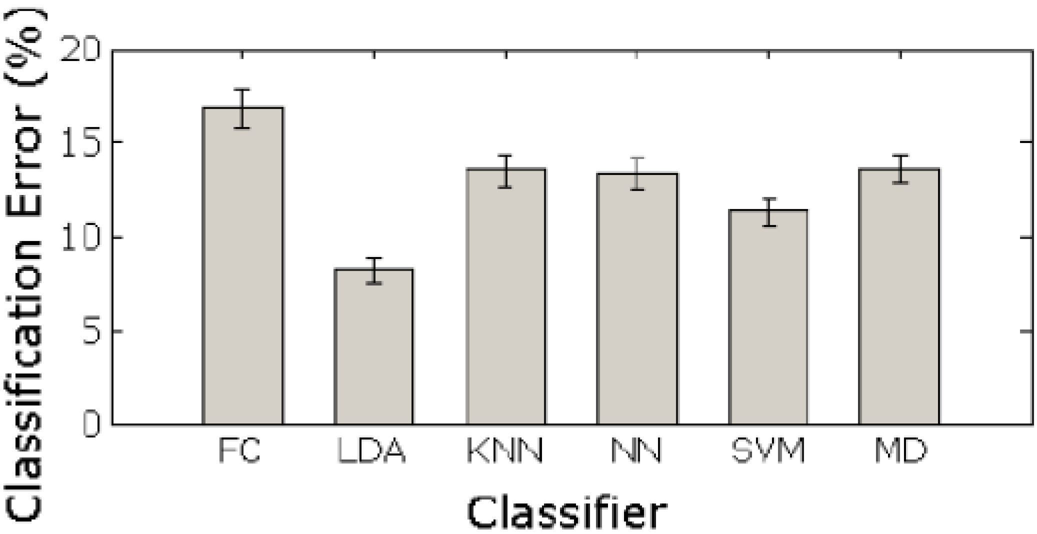
4.7. K-nearest neighbor (KNN)

The basis of this approach is that each sample is classified based on the class of their k Nearest Neighbors (KNN). This technique is a twofold process that first identifies the nearest neighbors and then classifies the input by majority voting or by distance weighted voting. The last method gives more relevance to the nearest neighbors by using the inverse or negative exponential of the Euclidean distance as weights. The main advantage of KNN is thus, its easy implementation.
However, KNN require training data during run time to compare the testing samples, and large training data sets may diminish real-time performance. Indeed it is quite vulnerable to irrelevant or redundant features, but dimensionality reduction and neighbor weighting have efficiently solve this problem.

Purushothaman and Ray proposed a prosthetic hand motion control using continuous EMG signals. Six hand and wrist movements were recorded with four EMG channels. Both TD and fourth order AR features were calculated and dimensionally reduced by PCA. The study compared pattern recognition performance of KNN and NN for both sets. The multilayer NN was built with five input and six output neurons and implemented for back-propagation training algorithm. Results revealed a higher average classification accuracy for TD features with KNN (84.3%) than with NN (80.8%). On the other hand, AR features were not quite accurately classified with neither KNN (59.1%) nor NN (63.5%).

4.8. Comparison of classifiers

Several studies have been conducted to compare the performance of different classifiers. For instance, Kaufmann et al. compared conventional classifiers with Evolvable Hardware (EHW) to recognize eight to eleven hand movement patterns based on EMG signals from forearm muscles. The tested classifiers were: KNN, MLP, SVM, Decision Trees (DT, based on fuzzy logic) and EHW. The latest is a new adaptable classification method, based on a programmable logic array like-structure that is optimize with evolutionary or genetic algorithms. Results of the experiment in which five recording sets were used for training and one for testing, show that SVM is the most accurate classifier with an average misclassification error of 9%, closely followed by MLP and KNN with 10.44% and 10.45%, respectively.
Radman et al. evaluated various feature combinations and classifiers for pattern recognition methods in dynamic myoelectric control systems. The classifiers employed were: KNN, SVM, NN, Fuzzy Clustering (FC or FIS according to the nomenclature of this chapter), LDA and Mahalonobis Distance (MD), similar to the Euclidean distance but taking onto account correlation in the data. Eight hand motions were recorded changing position, orientation and load to recreate more realistic conditions. Results of the classification error taking into account each feature set, show an increase in performance from FC, MD, KNN, NN, SVM and LDA, see Fig.30.Hence, due to its high accuracy and easy implementation, LDA was considered ideal for real-time applications.



4.9. Compination Of Classifiers

The previous methods are the main classifier techniques employed in myoelectric pattern recognition. However, some researchers have studied the performance of combined classifiers in order to compensate the weaknesses of each method and refine their performance. The major approaches in classifier combination are according to:

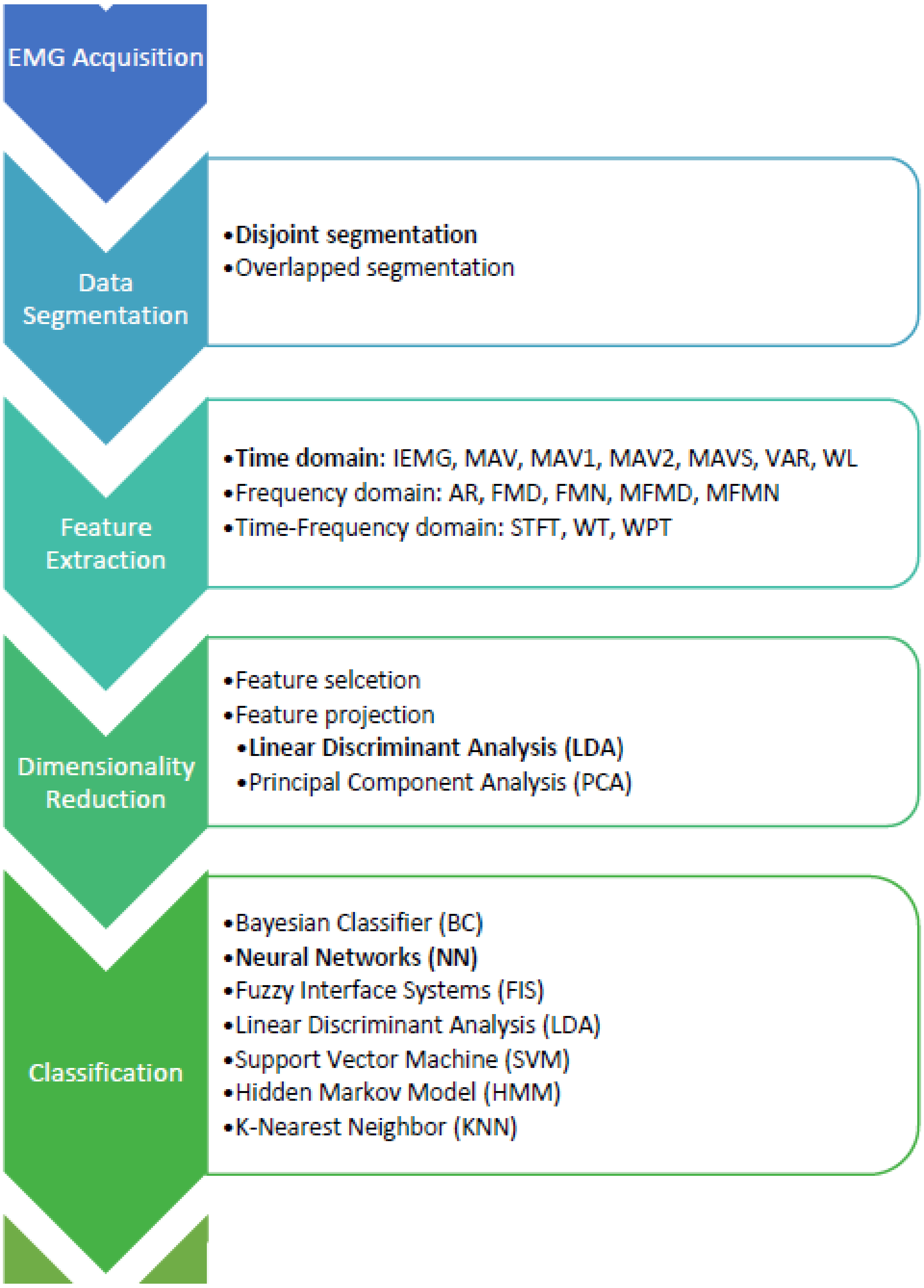
1. Parallel architecture: individual classifiers are applied independently and their outputs are then combined by a combiner to retrieve the final class, based on major voting for instance. Fariman *et al.* designed a hybrid Adaptive Resonance Theory (ART)-based neural network to classify upper limb myoelectric signals. ART is a supervised learning method of the NN. The proposed hybrid classifier (Best ART) employed four ART-based classification methods in parallel. The combiner algorithm is based on the classification accuracy of each independent classifier and the maximum rule to select the output with highest estimated confidence as final class. [46] Best-ART approach classification performance was tested against the four ART-based classifiers independently, KNN and LDA. Results show that Best-ART has the highest average classification accuracy (89.09%) and best computation time requiring less than half of LDA or KNN training and processing time.

2. Cascading architecture: individual classifiers are employed in a linear sequence to compensate the errors and refine the accuracy of the preceding classifier. Karlik et al. applied this architecture to design a neuro-fuzzy classifier called fuzzy clustering network (FCNN). Firstly, this method employs fuzzy clustering to divide the data into six overlapping clusters representing six upper limb motions. This algorithm estimates the center of each class and assigns input data a certain degree of membership. This clustered data of fuzzy cluster centers is used as input to the NN to retrieve a final classification value. The study compared classification performance of FCNN, MLP and Conic Section Functional Neural Network (CSFNN, variation of MLP that not only takes into account open boundaries but also class centers) with four AR parameters and signal power as features. Results show a maximum classification accuracy of 88% for CSFNN, 97% for MLP

and 98% for FCNN. In addition, it was proved that FCNN required less training time than the other classifiers to obtain reliable results.

3. Stacked architecture: Several classifiers are combined so that their outputs estimate the possible clusters and then, they are used as training set of the stacked classifier. Final classification takes into account a combination of the outputs of stacked classifier and individual ones. Although this architecture offers high efficiency and flexibility in class separation, it is seldom used for EMG signal classification. An example of this architecture is presented in Xiong and Cherkassky who developed a combined SVM with LDA (SVM/LDA). This approach can be considered a generalization of SVM that takes into account both local and global properties (characteristic of LDA). The SVM/LDA classification performance was evaluated against SVM and LDA alone, with a synthetically generated twonorm data set (20 dimension for 2 classes with normal distribution and unit covariance matrix) [48]. 90% of this data set was used for training, while the remaining 10% was employed in testing. Results demonstrate that SVM/LDA has the highest performance with an average classification accuracy of 98.3%, compared to SVM (95.8%) and LDA (97.4%).

To conclude, summarizes the content of this chapter, showing the different steps involved in pattern recognition of a myoelectric control system, and the associated techniques for each step. The present thesis has been developed taking into account these theoretical bases to classify user’s motions in order to actuate a robotic hand. The employed methods are in bold in Fig.31.



EMG Acquisition
Data Segmentation
•Disjoint segmentation
•Overlapped segmentation
Feature Extraction
•Time domain: IEMG, MAV, MAV1, MAV2, MAVS, VAR, WL
•Frequency domain: AR, FMD, FMN, MFMD, MFMN
•Time-Frequency domain: STFT, WT, WPT
Dimensionality Reduction
•Feature selcetion
•Feature projection
•Linear Discriminant Analysis (LDA)
•Principal Component Analysis (PCA)
Classification
•Bayesian Classifier (BC)
•Neural Networks (NN)
•Fuzzy Interface Systems (FIS)
•Linear Discriminant Analysis (LDA)
•Support Vector Machine (SVM)
•Hidden Markov Model (HMM)
•K-Nearest Neighbor (KNN)

CHAPTER 7

7. UML Diagrams

7.1. System Requirements

- System requirements, which were agreed upon by the entire project working group were the following: Multiple input file formats: European data format (EDF) and EDF+, textual format for signals and annotations, images formats. Files that contain metadata (anamnesis, disorder annotations, etc.)

- Biomedical time-series feature extraction – features would be chosen by:

1) A medical expert system implemented in the platform, which would be based on current medical knowledge from guidelines and relevant scientific papers,

2) An expert user, manually; a large number of features need to be supported by the platform, both general and domain specific biomedical time-series features.

- Feature selection methods, classification, regression, and prediction machine learning algorithms should be used to construct accurate subject state models.

7.2. Use Case Diagram

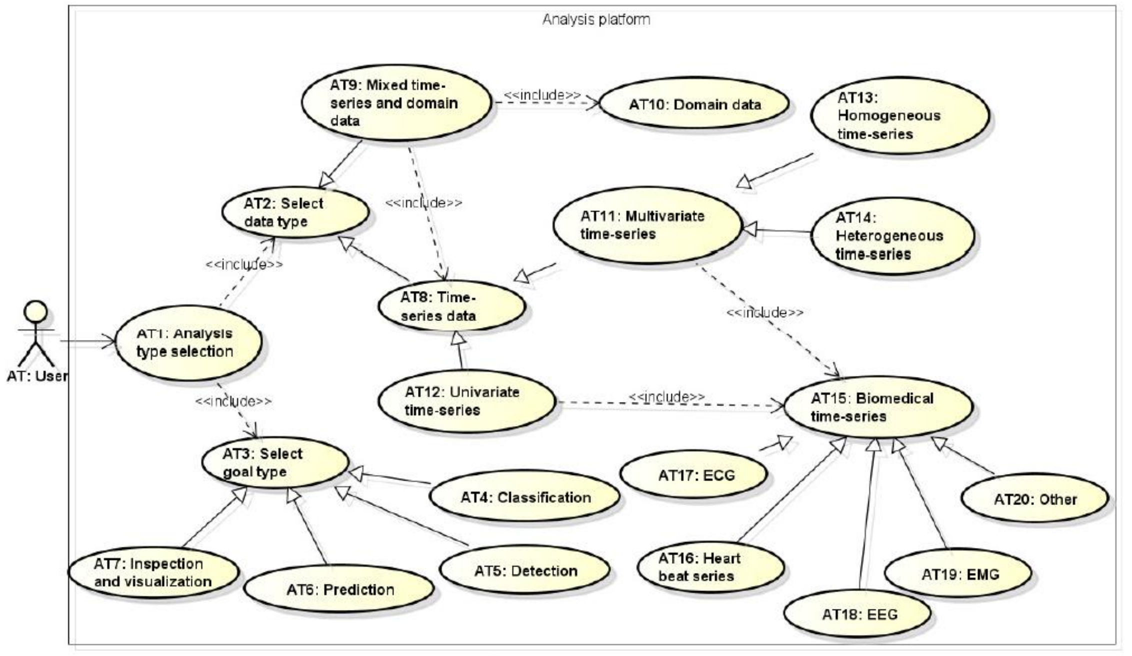
There were eight UML Use Case Diagrams that we identified, which describe the phases of the analysis:

1. Analysis type selection
2. Scenario selection
3. Input data selection
4. Records inspection
5. Records preprocessing
6. Feature extraction
7. Model construction
8. Reporting

Additionally, the 9. Diagram, User account, depicts registration, login and profile management. Finally, the 10. Diagram, Platform administration, shows the administrative access to the web platform. In the subsequent subsections, we present the diagrams and their detailed explanation.

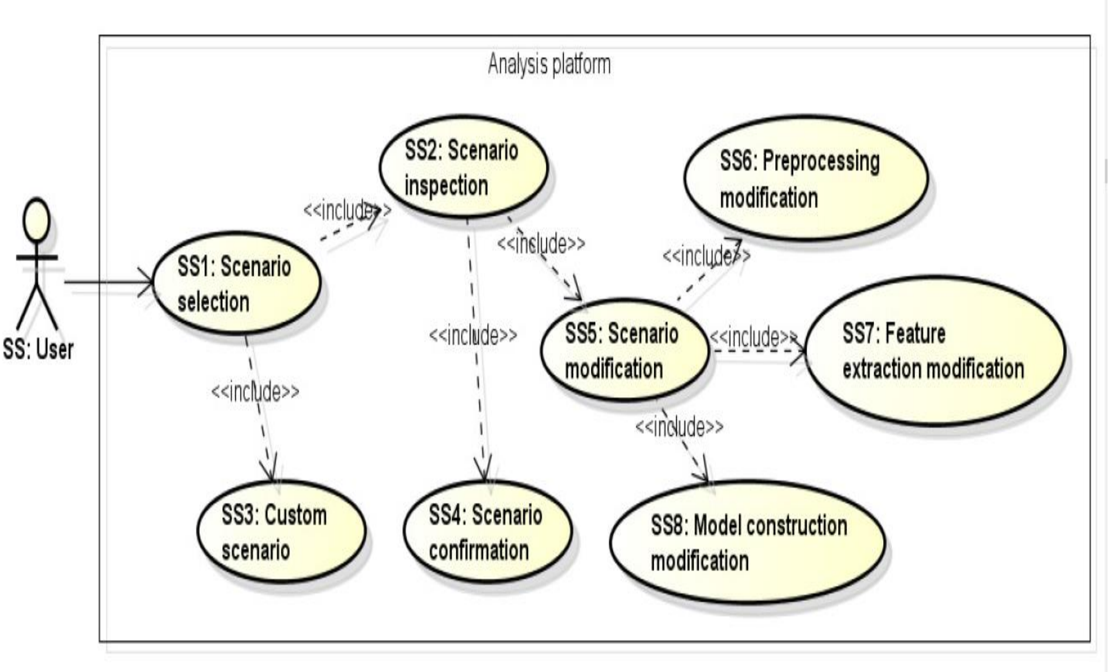
1. Analysis Type Selection

Analysis type selection, Fig.32, is conducted in a way that a user chooses the goal for an analysis that he wants to perform: detection, classification, prediction, or inspection and visualization. He also chooses the data type on which the analysis will be based. The data type may include exclusively biomedical time-series or biomedical time-series with additional domain data (e.g. subject anamnesis, metadata which describes record type, etc.). Biomedical time-series may be univariate by type, which means that there is only a single measured data array available in the record, e.g. the times of heart beats, or multivariate, which means that there are several measured data arrays present in the record. Additionally, multivariate data may he homogeneous, which means that they come from the same source measurement device, e.g. EEG data, or heterogeneous, which means that there are more than one measurement device involved at the same time, e.g. ECG + HRV + systolic ABP. An example of analysis type selection would be classification based on EEG data.



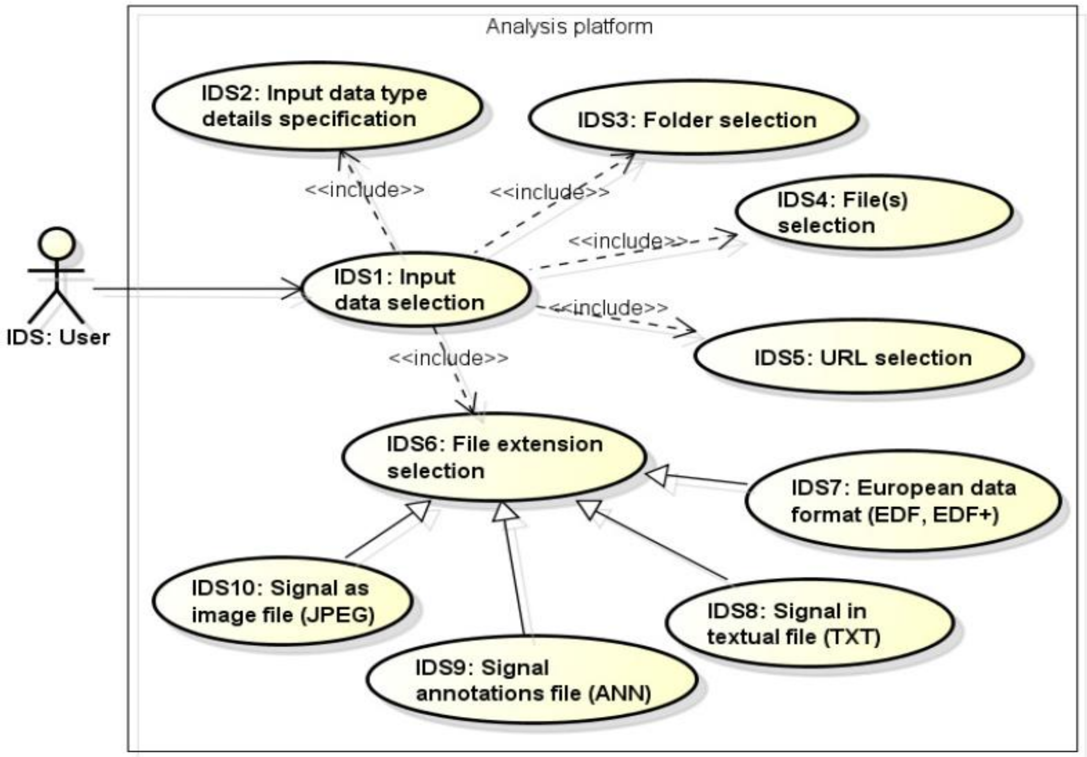
2. Scenario Selection

Scenario selection Fig.33 enables the user to select a predefined scenario, based on previously selected analysis type. It also allows the construction of a completely new scenario through full customization. A list of predefined analysis scenarios with all of the corresponding aspects (used components) will be provided to the user. The user will be able to confirm a scenario or change some of its aspects, such as preprocessing methods, feature extraction methods or model construction methods. When defining a new custom scenario, or changing an existing scenario, the user will be able to select any of the methods for accomplishing his goals. The predefined scenarios will contain features that are to be extracted from signals, which will be selected by the medical expert system specifically designed for this purpose. The medical expert system will be implemented based on current relevant medical guidelines, standards, and relevant medical and biomedical engineering literature. An example of a scenario would be to detect epilepsy in EEG, using wavelet transform modulus maxima and correlation dimension features, and a C4.5 decision tree.



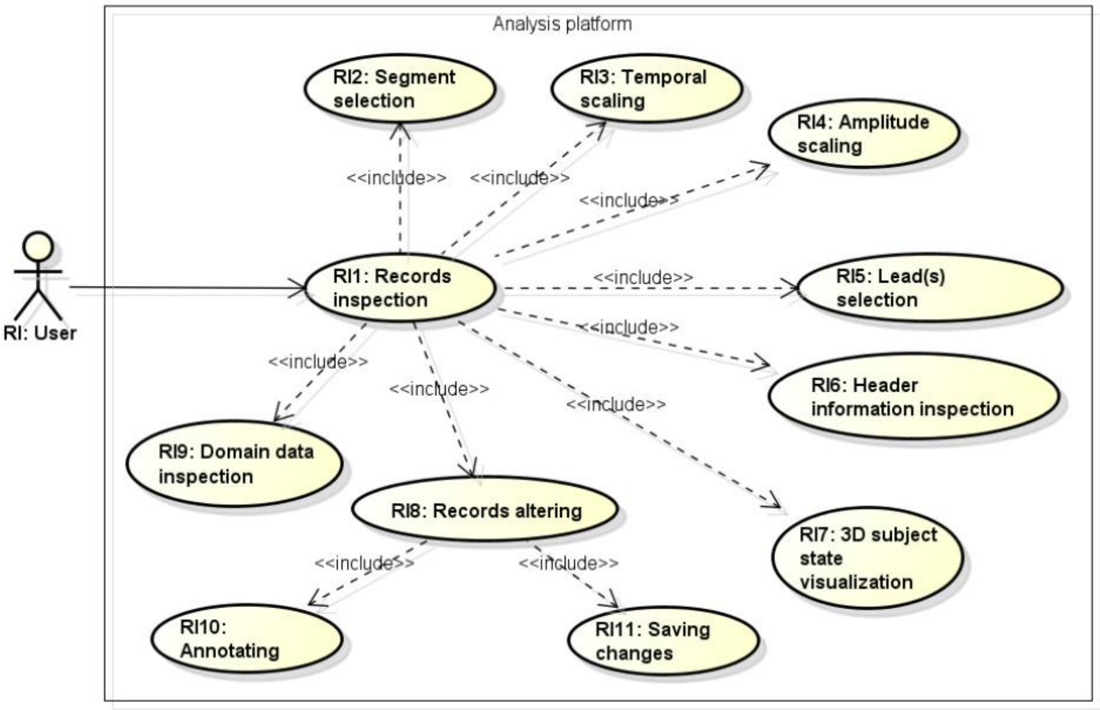
3. Input Data Selection

Input data selection, Fig. 34, includes the choice of file extensions (or file formats) that will be uploaded for the analysis. These formats include EDF, EDF+ (with or without annotations), separate textual annotation files (e.g. heart beat annotations), and textual raw signal files (without annotations) and image files (e.g. JPEG, TIFF). The user will have to select the appropriate file format in order for file upload to work without errors. Aside from selecting the format, the user also specifies the files that will be uploaded or selects the folder from which all the required files can be found. If there are some specific details related to records loading into platform (e.g. only partial file loading, limitations for some image formats, etc.), these can also be specified during this phase.



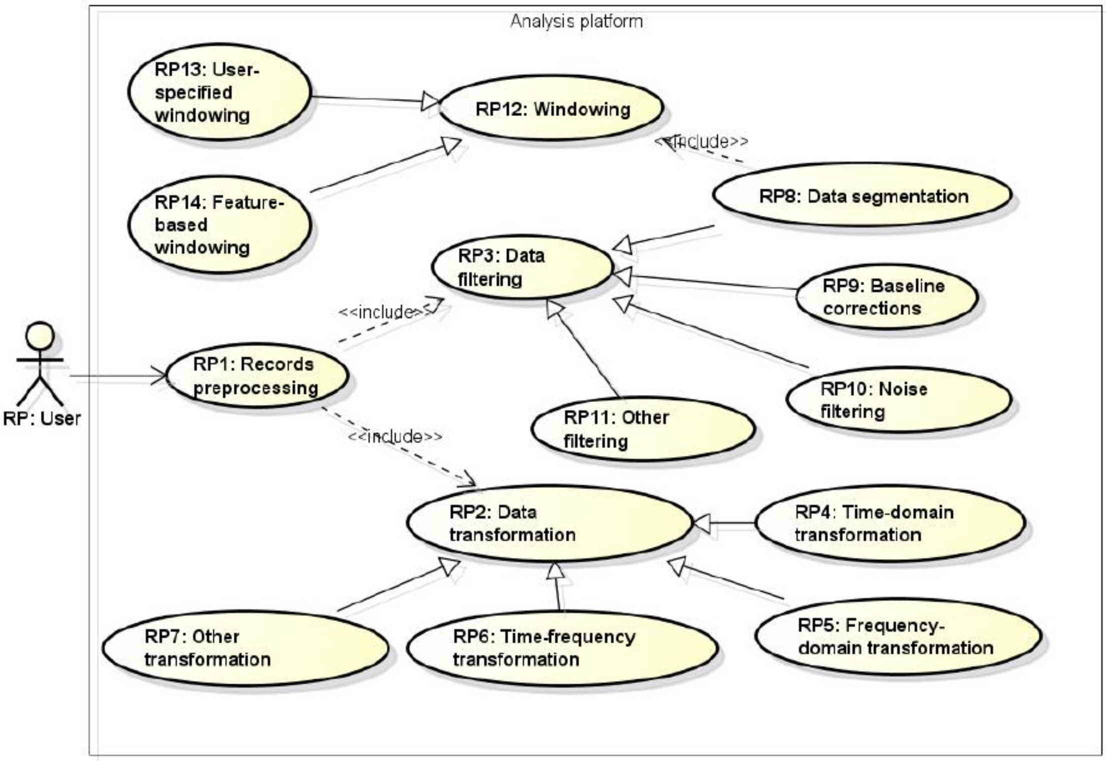
4. Records Inspection

After the records are uploaded into the platform, it will be possible to inspect and visualize (Fig. 35) each loaded record through the platform's graphical user interface. Here, the user will be able to: select specific record segment, select temporal and amplitude scaling of the signals, display some or all of the signal trails (arrays), inspect record headings and domain data (if such information exists). 3D visualization will be enabled for certain specific states for some biomedical signals (e.g. visualization of myocardial infarction location based on ECG). Additionally, the user will be able to annotate some of the available signals or change the existing annotation files and save these changes.



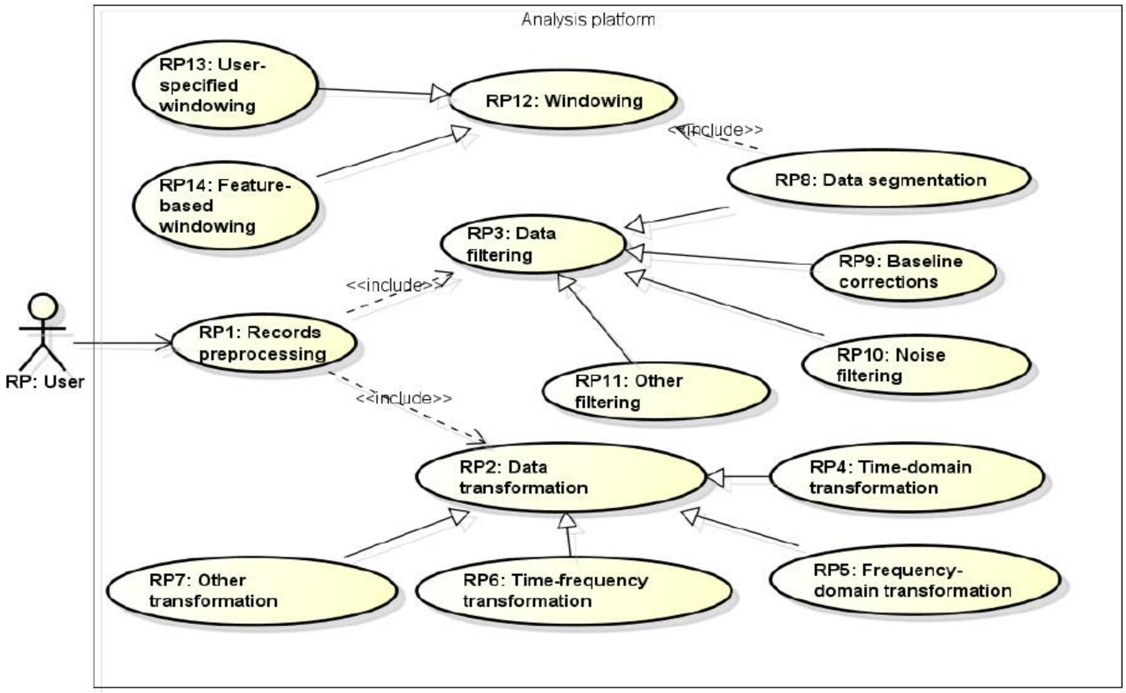
5. Records Preprocessing

Records preprocessing, Fig. 36, assumes various procedures for signal filtering and data transformations. Signal filtering includes noise filtering (e.g. notch filters for 50 / 60 Hz), baseline wandering corrections (e.g. for ECG because of breathing, body movements or electrodes impedance changes), records segmentation into windows of certain width. Window width may be chosen by the user or it may be implicit, determined by the very features that are to be extracted (e.g. a single RR interval for detailed ECG analysis). Other filtering methods include various linear and nonlinear filtering procedures with the goal to obtain higher quality signals. Data transformations will be performed after the filtering procedures and will include various time (e.g. principal component analysis - PCA), frequency (e.g. fast Fourier transform, Hilbert Huang transform), time frequency (e.g. wavelet transform) and other types of data transformations. The goal of data transformations is to obtain the data in a form from which it is easier to calculate precise domain or general features for describing specific subjects' states.



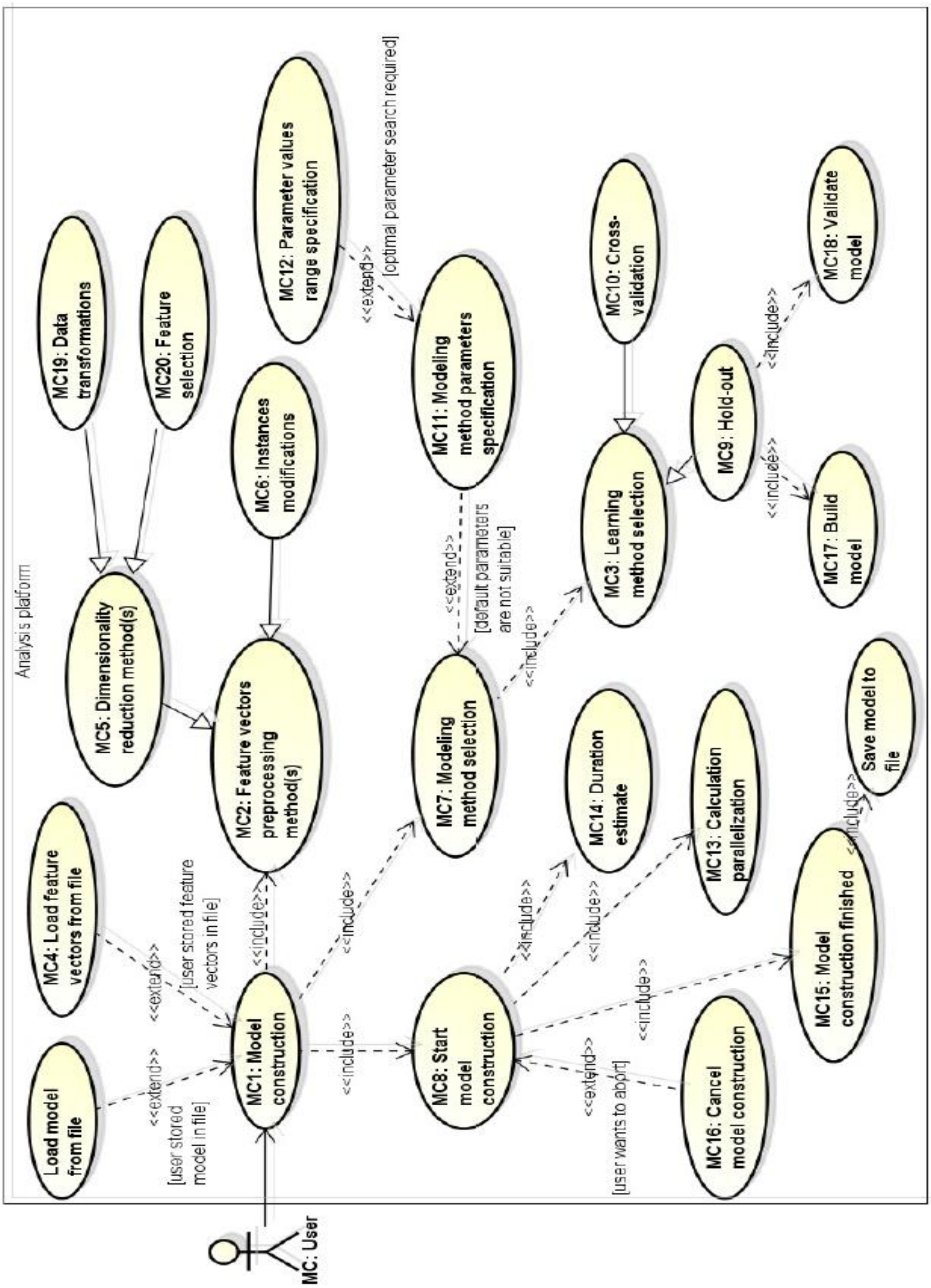
6. Feature Extraction

Feature extraction, Fig. 37, is the central step in the analysis of biomedical time-series. The user will already be provided with a list of features in the scenario selection phase. Regardless of the scenario, in the feature extraction phase, it will be possible so select additional features and specify parameters for calculation of a particular feature, for those features that are parametric. When starting feature extraction, the user will be able to inspect the information about the estimation of the analysis duration and will be able to modify the type of calculation parallelization that will be performed. It will be possible to cancel feature extraction execution at any time. The user will be allowed to save the extracted feature vectors in a file for future analysis, if he wants to have the intermediate results recorded.



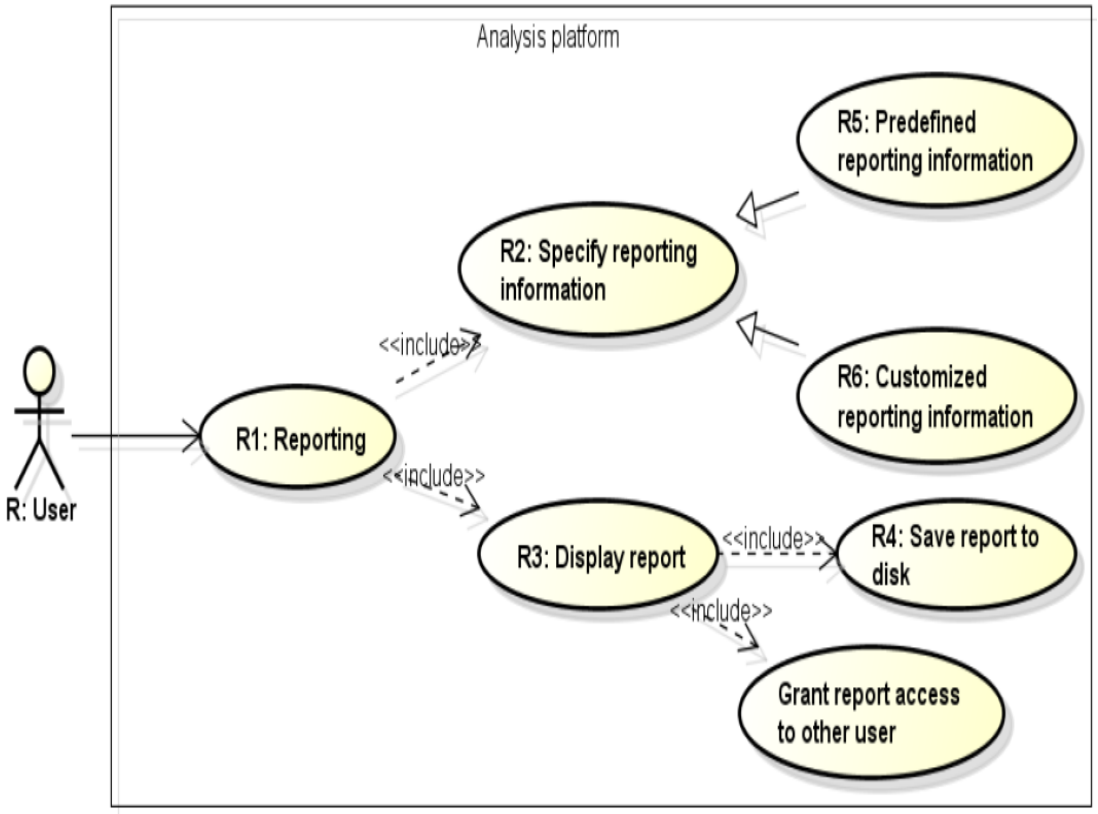
7. Model Construction

Model construction, Fig. 38, is a complex step in the analysis of biomedical time-series that takes place after feature extraction and includes various machine learning algorithms for the analysis of the extracted feature vectors. In this step, the user will be able to load the file with feature vectors that were calculated and saved earlier and resume the analysis or continue the analysis from the recently obtained and unrecorded extracted feature vectors. Model construction phase starts with the option to select feature vectors' preprocessing methods. Herein, one can use feature vectors' dimensionality reduction methods such as various transformations (e.g. PCA) or feature selection methods (filters, wrappers, embedded, and other methods). Dimensionality reduction is necessary in the case where a large number of features were extracted (either by the choice of the expert system or by the user's selection). The goal of dimensionality reduction is to keep only relevant and non-redundant features in order to improve speed and accuracy of model construction. Aside from feature space dimensionality reduction, it will be possible to use some methods to alter the feature vectors themselves (e.g. resampling, missing values replacement, etc.). After the feature vectors preprocessing step, the user will be able to select a model construction method. During this step, first a method is selected and then, the method parameters are defined. Method parameters selection will be made possible if the modeling method is parametric (e.g. C4.5 decision tree, random forest). Before starting model construction, it is necessary to specify the learning method that will be used: holdout Procedure, where a part of dataset is used training and the other part for testing, or cross-validation, where testing is performed on dataset segments so that all the dataset is eventually used for testing. It will also be possible to perform only model testing on a set of new samples, if there is a model present in the system that was trained earlier on the same feature set. When starting model construction, the user will be able to inspect the information regarding the estimation of the construction duration and will be able to modify the type of computing parallelization that will be performed. The construction procedure could be cancelled at any time. After model construction, it will be made possible to save the trained model into a file for later use.



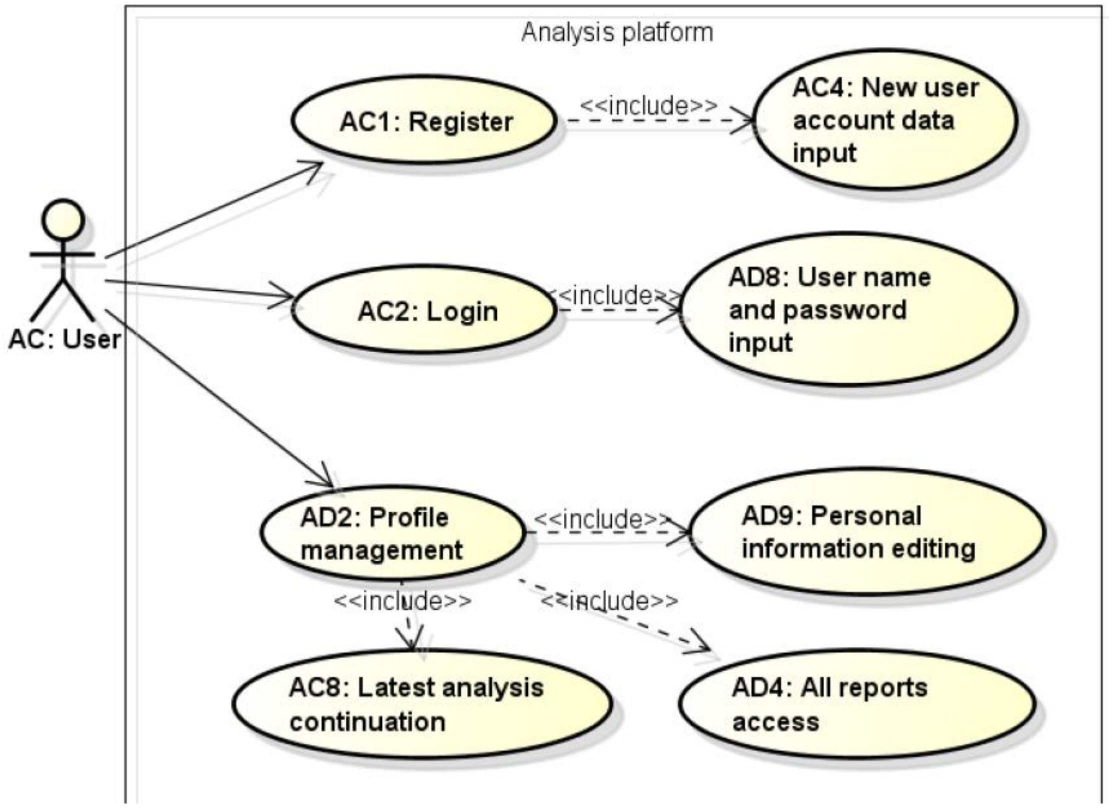
8. Reporting

Reporting, depicted in Fig. 39, is the step in which a user chooses the way in which the results of the analysis are displayed. Thereafter, the report is displayed in the selected form (on a web page only, in PDF, MS Excel, Word or ODF form). It will be possible to save the copy of the report onto the client's computer, whereas its copy will be stored on the server. Additionally, the user will be able to grant access to the report to other registered users, at his convenience.



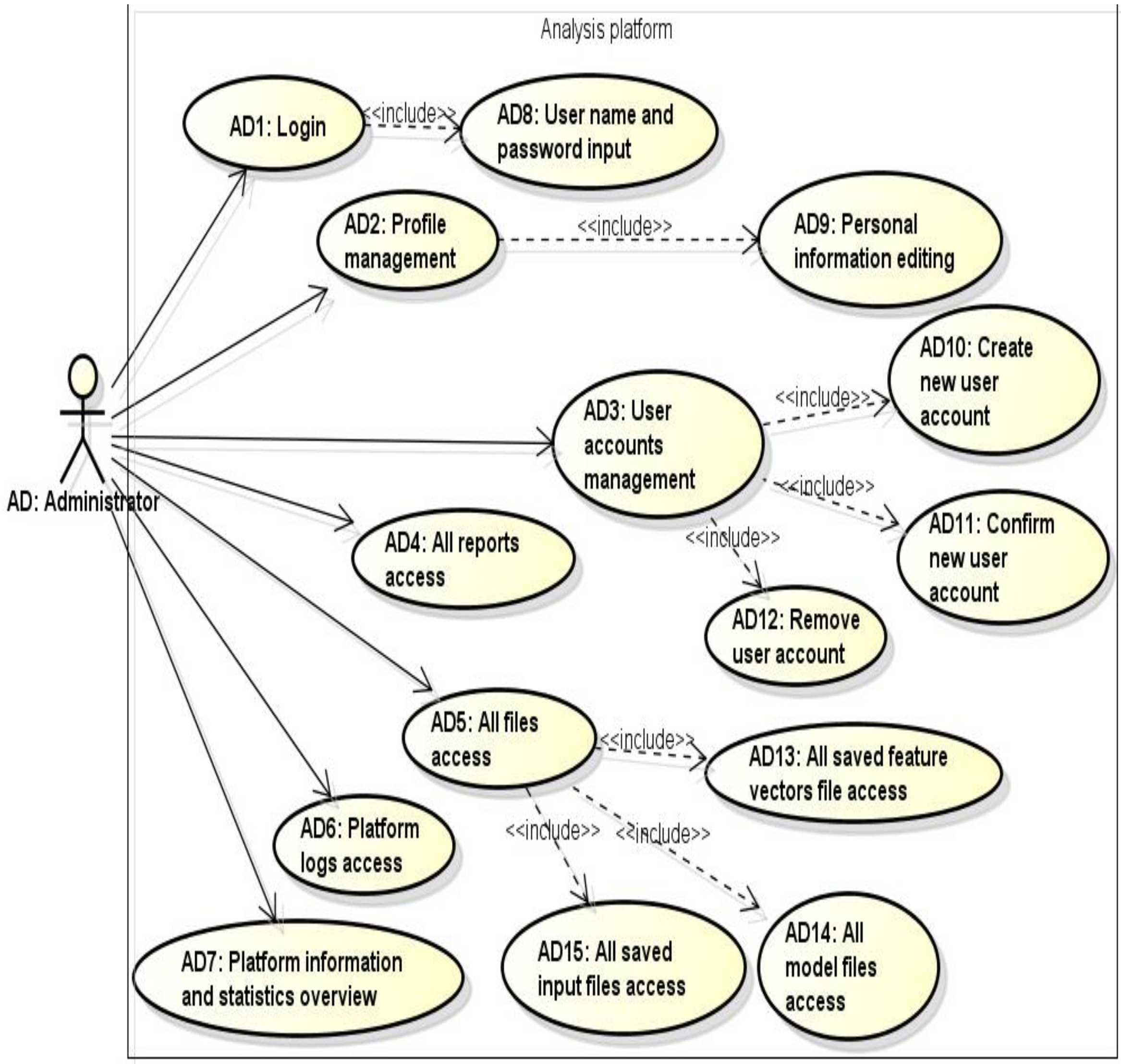
9. User Account

An account for a new user will be opened by registering the user onto the platform, which will include entering the data about the user (necessary data: user name, password and e-mail address; additional data: first and last name, title, affiliation, affiliation's address, telephone), Fig. 40. Logging into the system will be allowed after confirmation that the registration was accepted. Profile management will be enabled after a successful login. It will include editing personal information, accessing generated (finished) reports that are linked to the user or resuming the last analysis conducted by the user.



10. Platform Administration

Platform administrator will have to login into the platform in the same way as the user, by entering his user name and password, Fig. 41 . The administrator will have at his disposal a number of options. First, he will be able to edit his personal profile. He will also be able to manage user accounts for all the platform's users. This will include opening a new user account (as if a user has registered), confirming the registration of a new user, and removing an existing user account. For each account, administrator will be able to inspect the user's personal information (except password), without the possibility of modification. The administrator will be able to inspect and search all of the reports generated in the platform. Also, he will be allowed access to all of the other files stored in the system, including all the saved input files, all the feature vectors files, and all the constructed models file. He will be able to delete them at his convenience. Moreover, the administrator will have access to all platform's logs, which will be sorted by date. The logs will contain relevant information about the users' actions during the use of the platform. Additional information about the platform as well as its usage statistics will also be at his disposal.


Analysis platform
AD1: Login
<<include>>
AD8: User name and password input
AD2: Profile management
<<include>>
AD9: Personal information editing
AD10: Create new user account
<<include>>
AD3: User accounts management
<<include>>
AD11: Confirm new user account
<<include>>
AD: Administrator
AD4: All reports access
AD12: Remove user account
AD5: All files access
<<include>>
AD13: All saved feature vectors file access
<<include>>
<<include>>
AD6: Platform logs access
AD7: Platform information and statistics overview
AD15: All saved input files access
AD14: All model files access

CHAPTER 8

8. Conclusion And Future Work

8.1. Conclusion

Important issues to consider when designing an sEMG interfaceare related to acquiring sEMG signals with electrodes, as well asfiltering, segmentation, feature extraction and classification of thesEMG signal. Because the general recommendations for electrodeconfigurations, presented for example by SEMIAM, are designedfor measurements in laboratory conditions, they may not always beoptimal for sEMG interfaces where the purpose is robust signal clas-sification during long-term use in real use environments. Relativelyglobal sEMG measurements from a muscle group have been foundto include sufficient discriminatory information for successful classification. Thus, it is not always necessary to target the electrodesto specific sites on single muscle(s); it can be enough to place elec-trodes on the muscle group of interest. The optimal number of sEMGchannels for hand and forearm posture recognition can vary, but itis suggested to be between four and six bipolar channels. The rec-ommended electrode size is about 1 cm × 1 cm or 2 cm × 2 cm. Ifelectrode shifts are present, higher classification accuracy may beachieved by increasing the inter-electrode distance from the generally used distance of 2–4 cm. HD-sEMG with arrays of multipleelectrodes provides a promising alternative to conventional bipo-lar measurements since it allows designing sEMG interface that isrelatively tolerant against electrode displacements and does notrequire re-training if malfunctioning electrodes are removed during the use of the sEMG interface. In HD-sEMG systems the IEDshould be below 10 mm to avoid spatial aliasing. However, the optimal sEMG setup is muscle-, muscle-group-, and task-specific, andthus need to be customized for the purpose used**.**

Because most of the energy of sEMG signal is below 400–500 Hz,sEMG studies have usually adopted the sampling rate of 1000 Hzand the high-pass cutoff frequency of 20 Hz. However, recent evi-dence suggests that an accurate classification is possible with amore narrow frequency range, with sampling at 500 Hz and high-pass cutoff at 60 Hz. With these values, the processing time andthe need for memory can be halved. The classification accuracy ofthe sEMG system may be further improved by using preprocessingalgorithms, such as ICA and PCA.

Delay should be minimized in real-time sEMG applications.Equations have been presented to estimate the worst, average andbest case delays as well as delay ranges. A delay is a function of thewindow length, processing time, amount of window overlap, andthe number of majority votes used. Shortening the length of thesegments decreases classification accuracy. The theoretical minimum for a segment length is 200 ms, but shorter segments can beused with MV. No obvious difference exists in classification accuracy whether it is used a large window with a small number of votesor a small window with a large number of votes, but less storagespace is needed in the latter case. Overlapped segmentation is theoptimal segmentation strategy. Although classification relying onsteady-state information has been shown to be superior

comparedto classification based on transient data, dynamic portions of EMGsignals also are important for real myocontrol systems and thusmust be included in the learning process in order to achieve highoverall classification accuracy.sEMG commands can be decoded using pattern recognition-based methods or non-pattern recognition-based methods, andalso both of them can be adopted in the same system. Non-pattern based methods are more simple to implement and may be effec-tive in navigation menus, wheelchairs, and assistive robots. If thepurpose is to control multiple DOFs, pattern recognition-basedmethods are more appropriate. However, today most studiesconcentrate on the pattern recognition-based control approachbecause it allows a more versatile user interface. The recommended classifier in sEMG interfaces is LDA, because it does notrequire any parameter adjustment, is computationally efficientand robust and yields similar classification accuracy to that ofmore complex classification algorithms.The most critical step in sEMG signal processing is feature selection. The optimal feature set depends on the measurement systemas a whole as well as on the classification task. The A LDA classifierwith the TDAR feature set (i.e. MAV, WL, SSC, ZC and AR coefficients)has become a common combination in sEMG studies. The drawbackof TD features, however, is that they are based on signal amplitude,which makes them relatively sensitive to noise. FD features havepoorer classification accuracy than TD features but are suggestedas augmenting features for successful TD features to increase therobustness of the feature set. Extracting TD and FD features fromDWT coefficients or from the signal reconstructed after waveletdenoising may also increase the robustness. HD-sEMG, recentlyadopted in sEMG interfaces, allows the study of the sEMG signal inthe spatial domain, opening new possibilities to the field of sEMGcontrol.
sEMG interfaces have numerous applications, which can bedivided into four application areas: assistive technology, rehabilita-tion technology, input devices, and silent speech recognition. Mostresearch on sEMG interfaces has concentrated on the applicationsof assistive and rehabilitation technology, but in the recent yearsthe interest has also increased in sEMG applications for healthypeople. Examples of the applications where sEMG interfaces havebeen used include prostheses, exoskeletons, silent speech inter-faces, and armbands that replace traditional input devices.sEMG interface provides a totally new way of communicationthat will open up possibilities to comprehensive human–deviceinteraction. The advantages that it offers to the user over exist-ing control methods include subtle and intimate communication,independence of portable control devices, and avoidance of directeye contact or deep attention by the user. The major challengein developing the prototypes of sEMG applications to commercialproducts is to achieve robust classification in long-term use withoutmaking the classifier training procedure too cumbersome. Whilerelatively simple classifiers and feature vectors have been sufficientto provide high classification accuracy in laboratory conditions,the future trend in sEMG studies seems to be toward more complicated control systems, such as conditional parallel classifiers,regression-based methods, signal factorization as well as utiliza-tion of online training and sensor fusion (i.e. using sEMG with othersensor modalities) that are likely to allow more robust and versatileuser interface.

A two channel EMG pattern recognition system was proposed in this paper to classify individual and combined finger movements. Various features were extracted from the two channels and reduced in dimensionality using PCA. In order to enhance the output classification decisions made by the current EMG pattern recognition system, a support vector machine postprocessing was proposed to remove spurious misclassification results and was compared with other postprocessing techniques utilized in EMG pattern recognition in the literature. Experiments conducted on EMG datasets belonging to ten different finger movements collected from eight subjects for the purpose of this research proved the feasibility of the proposed system using different classifiers achieving _98% offline and _90% online classification accuracy results with the LIBSVM classifier and Bayesian fusion. The current results suggest the success of the two EMG channels system in classifying ten different individual and combined finger movements.

A support vector machine (SVM) based EMG signal classification method has been designed in this work. The classification method starts with collected EMG data segmentation with a sliding window technique. Features are extracted using time-frequency domain feature representation for each sliding window. Among several window sizes suitable window has been selected by investigating their influences on the classification accuracy. Best feature set (i.e. feature parameters) that ensures maximum separation between finger movements has also been investigated. The classification accuracy of individual and combined finger movements using SVM based classifier is of **98 %** across all subjects. So it can be concluded that support vector machine based pattern recognition system is suitable for discriminating hand motions with the little cost of average classification rate.

8.2. Future Work

The formerly derived conclusions suggest several work lines to improve the present study, and bring closer the implementation of this technology in the real world, outside the laboratory.

The first and foremost proposal is to research towards the fulfillment of real-time requirements. As previously mentioned, PYTHON (SVM) Toolbox provide an extensive set of configuration parameters that can be evaluated to reduce the execution time; like the computational features associated to training functions, or applying instead a transfer function to map SVM input data into their corresponding output.

However, changing these parameters may affect the classification accuracy and generalization of the SVM classifier. Hence, further analysis should be carried out to clearly assess the crucial parameters, from both input data and SVM, involved in SVM performance and how they affect the elapsed time. Special considerations should be taken into account regarding dimensionality reduction algorithms and their generated mappings as they are the base of the training process. Once all these specifications have been optimized, the next advisable step is their directly implementation into a microcontroller to reduce the execution time.

If none of the mentioned modifications of the SVM yield in an improvement of the control system, there are other classifiers that can be also examined and are already integrated in MATLAB environment like (NN, BC, KNN).

The present work requires EMG signal acquisition and SVM training for each session, which implies the placement of nine surface electrodes in the precise locations. This arrangement is not only tedious for the user but can also produce significant changes

in the recorded signals, reducing greatly the generalization ability of the classifier. Therefore, developing a unified recording system that integrates the nine electrodes and perfectly fits the subject, so that the electrodes are placed correctly and easily regardless the session, could be quite advantageous to the system.
To conclude, the present bachelor thesis can be interpreted as the first step towards the development of a robust, real-time, SVM-based control system in MATLAB/ Simulink. The present work has faced both promising results and severe problems; however the overall analysis of this chapter aims to provide a solid base to elucidate the advantages and drawbacks of this technology, to guide future work in this field and improve the model.

References

[1] Luca, Carlo J. De. “Physiology and Mathematics of Myoelectric Signals.”Biomedical Engineering, IEEE Transactions on BME-26.6 (June 1979): 313–325. Web. 31 Dec. 2015.

[2] Oskoei, M.A., and Huosheng Hu. “Support Vector Machine-Based Classification Scheme for Myoelectric Control Applied to Upper Limb.” IEEE Transactions on Biomedical Engineering 55.8 (Aug. 2008): 1956–1965. Web.

[3] Christodoulou, C.I., and C.S. Pattichis. “Unsupervised Pattern Recognition for the Classification of EMG Signals.” IEEE Transactions on Biomedical Engineering 46.2 (1999): 169–178. Web.

[4] Gut, R., and G.S. Moschytz. “High-Precision EMG Signal Decomposition Using Communication Techniques.” IEEE Transactions on Signal Processing 48.9 (2000): 2487–2494. Web.

[5] Kaur, G., A.S. Arora, and V.K. Jain. “Comparison of the techniques used for segmentation of EMG signals.” Proceedings of the 11th WSEAS international conference on Mathematical and computational methods in science and engineering. N.p.: World Scientific and Engineering Academy and Society (WSEAS), 2009. 124–129. Web.

[6] Karlsson, S., Jun Yu, and M. Akay. “Time-Frequency Analysis of Myoelectric Signals during Dynamic Contractions: A Comparative Study.” IEEE Transactions on Biomedical Engineering 47.2 (2000): 228–238. Web.

[7] Phinyomark, A., C. Limsakul, and P. Phukpattaranont. “A Novel Feature Extraction for Robust EMG Pattern Recognition.” Journal of Computing1.1 (Dec. 2009): n.pag. Web. 28 Jan. 2016.

[8] Fodor, I K. A Survey of Dimension Reduction Techniques. Springfield, United States: Lawrence Livermore National Laboratory, 9 May 2002. Web. 18 Jan. 2016.

[9] Liu, Jie. “Feature Dimensionality Reduction for Myoelectric Pattern Recognition: A Comparison Study of Feature Selection and Feature Projection Methods.” Medical Engineering & Physics 36.12 (1 Jan. 1716): 1716–1720. Web. 18 Jan. 2016.

[10] Mitchell, T. M. “Bayesian Learning.” Machine learning. New York: McGraw Hill Higher Education, 1 Apr. 1997. 156–158. Print.

[11] Bu, N., M. Okamoto, and T. Tsuji. “A Hybrid Motion Classification Approach for EMG-Based Human–Robot Interfaces Using Bayesian and Neural Networks.” IEEE Transactions on Robotics 25.3 (June 2009): 502–511. Web.

[12] Haykin, S. “Introduction.” Neural networks and learning machines: A comprehensive foundation. Ed. M. J. Horton. Harlow: Prentice Hall, 18 Nov. 2008. 1–46. Print.

[13] Ahsan, Md. R., M. I. Ibrahimy, and O. O. Khalifa. “Neural Network Classifier for Hand Motion Detection from EMG Signal.” 5th Kuala Lumpur International Conference on Biomedical Engineering 2011. Ed. Noor Azuan Abu Osman, Wan Abu Bakar Wan Abas, Ahmad Khairi Abdul Wahab, and Hua-Nong Ting. Kuala Lumpur, Malaysia: Springer Science + Business Media, June 2011. 536–541. Web.

[14] Sivanandam, S. N., S. Sumathi, and S. N. Deepa. Introduction to Fuzzy Logic Using MATLAB. Berlin: Springer-Verlag Berlin and Heidelberg GmbH & Co. K, 3 Nov. 2006. Print.

[15] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stub-blefield, and K. B. Englehart, “Targeted Muscle Reinnervation for Real-time Myoelectric Control of Multifunction Artificial Arms”, The Journal of the American Medical Association, vol. 301, no. 6, pp. 619-628, 2009.

[16] B. Hudgins, P. Parker, and R. N. Scott, “A new strategy for multifunction myoelectric control”, IEEE Transactions on Biomedical Engineering, vol.40, no.1, pp. 82-94, 1993.

[17] K. Englehart and B. Hudgins, “A robust, real time control scheme for multifunction myoelectric control”, IEEE Transactions on Biomedical En-gineering, vol. 50, no. 7, pp. 848-854, 2003.

[18] M. A. Oskoei and H. Hu, “Support Vector Machine-Based Classification Scheme for Myoelectric Control Applied to Upper Limb”, IEEE Transac-tions on Biomedical Engineering, vol. 55, no. 8, pp. 1956-1965, 2008.

[19] M. A. Oskoei and H. Hu, “Myoelectric control systems-A survey”, Biomedical Signal Processing and Control, vol. 2, no. 4, pp. 275-294, 2007.

[20] F. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, and N. V. Thakor, “Toward the Control of Individual Fingers of a Prosthetic Hand Using Surface EMG Signals”, Proceedings of the 29th Annual Inter-national Conference of the IEEE EMBS, pp.6146-6149, 2007.

[21] R. J. Smith, D. Huberdeau, F. Tenore, and N. V. Thakor, “Real-Time Myoelectric Decoding of Individual Finger Movements For a Virtual Target.

[22] M.A. Oskoei,H.Hu,Myoelectriccontrolsystems—a survey, Biomed. SignalProcess.Control2(4)(2007)275–294.

[23] M. Zecca,S.Micera,M.C.Carrozza,P.Dario,Control of multifunctional prosthetichandsbyprocessingtheelectro- myographic signal,Crit.Rev.Biomed.Eng.30(4–6) (2002) 459–485.

[24] J.R. Wolpaw,N.Birbaumer,D.J.McFarland,G.Pfurtscheller, T.M.Vaughan,Brain–computer interfacesforcommunication and control,Clin.Neurophysiol.113(6)(2002)767–791.

[25] L. Sörnmo,P.Laguna ,Bioelectrical Signal Processing in Cardiac and Neurological Applications ,Elsevier Academic Press, United States ofAmerica,2005.

[26] C.I. Christodoulou,C.S.Pattichis,Unsupervised patternrecog- nition for the classification of EMG signals ,IEEETrans.Biomed. Eng. 46(2)(1999)169–178.

[27] R. Gut,G.S.Moschytz,High-precisionEMGsignaldecomposi- tion usingcommunicationtechniques,IEEETrans.Signal Process.48(9)(2000)2487–2494.

[28] M.A. Oskoei,H.Hu,Supportvectormachine-basedclassifica-tion schemeformyoelectriccontrolappliedtoupperlimb, IEEE Trans.Biomed.Eng.55(8)(2008)1956–1965.