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Surface Electromyography Signal Processing for Upper-limb Hybrid Assist-as-need Exoskeleton intended for Stroke Patients

Master's thesis conducted by

Eva Hansenne

in order to obtain the degree of Master in Biomedical Engineering

Under the supervision of

Dr. Chris Pretty
Pr. Thomas Desaive

Academic Year 2016-2017

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Abstract

Stroke, which is the second largest disability worldwide, may induce one side transient paralysis. The rehabilitation method is a key point for minimizing the time of recovery, for increasing the patient comfort or for decreasing the cost of stroke therapy for the society. This thesis aimed to process the raw surface electromyography (sEMG) signal coming from the biceps to extract useful information to trigger an actuator combined to a exoskeleton or to apply functional electrical stimulation (FES) for stroke rehabilitation. Thus, the FES/actuator triggering will be assist-as-needed.

The data acquisition was first performed using an sEMG prototype circuit. The sEMG signal was recorded at a given sample frequency (1 kHz) and was displayed in real-time. Several kinds of surface electrodes were tested and characterized.

Next, several muscle activity evaluations were analysed to find the most appropriated. The sEMG signal in presence in FES was recorded. It has been shown the alteration of the stimulation artifacts and the need of further analysis to remove them for providing consistent data.

Finally, interesting information such as intention, force and fatigue estimation were extracted from the sEMG signal in real-time. Intention is the time activation of a muscle and can be used to trigger FES or to control the actuator. Force estimation is the signal normalisation according to a reference providing an estimation of the force exerted by the muscle. This data provides a proportional indication for FES or the actuator. From the sEMG signal, localized muscular fatigue was assessed. This may optimize the rehabilitation session and may also track the patient progress. Some characteristics of sEMG signal during an elbow flexion/extension movement were studied.

Academic Year 2016-2017

Acknowledgement

I would like to thank all those who helped, advised and encouraged me during this project and all along these five years of study.

I would like to express my gratitude to Pr. Thomas Desaive and Dr. Chris Pretty for giving me the opportunity to spend five months in New-Zealand and the experience to live abroad. Thanks for guiding me, your availability all along my work and your time spent .

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Chapter 1

Introduction

Stroke, also named cerebral vascular accident, occurs when blood supply to some parts of brain is insufficient. This lack of blood induces a lack of oxygen and causes injuries or death of brain cells. Stroke is the second largest disability worldwide after demantia, one in six people will suffer a stroke during their lives [11]. Disability may often include one side transient paralysis (hemiplegia). To recover, patients who have survived a stroke have to follow a high number of rehabilitation sessions. Therefore, in order to minimize the recovery time, the cost of stroke therapy and to increase the patient comfort, it is important to develop effective rehabilitation methods. Indeed, rehabilitation approaches using repetitive and functional tasks reduce time needed to strength muscle and to enable daily life movements [12].

Several kinds of devices have been developed to help rehabilitate the stroke patient. The first ones, the simple ones, are passive devices including lockable and unlockable brakes or springs and strapping tape. The second type of devices are active devices. These ones are used to help patients to perform movement which are impossible for them to achieve by themselves with the use of actuator or functional electrical stimulation (FES). Active devices include exoskeletons. Exoskeletons allow patients to mimic natural human movement. An advantage of exoskeletons over other devices is that they offer an independent precise control of different joints. However, their portability is limited due to their energy requirements and the actuator weight.

FES elicits muscle contraction by means of high-frequency electrical pulse. The patients muscles are doing the work, so they do not atrophy. If an actuator does all the movement, the muscles do not grow. However, the use of FES induces muscle fatigue and pain for some patients.

Electromyography (EMG) records the electrical activity of muscles. EMG may be used to control and/or to initiate the exoskeleton actuator or FES. Indeed, for healthy patients and for many stroke patients as well, a movement attempt lead to muscle action potentials (MUAPs) in muscle(s) involved. MUAPs appear slightly before the movement and are readable using electrodes. Sometimes, patient have not enough strength to perform their intended movement and exoskeleton or FES could help to achieve it with information from EMG.

Ashley Stewart, the Ph.D. student I have assisted, is developing an upper-limb hybrid assist-as-need exoskeleton for the rehabilitation of the elbow (biceps/triceps muscles). By definition, hybrid skeleton combines the use of FES and an electromechanical actuator to provide assistive or resistive training. The choice of hybrid exoskeleton seems to be the most effective method for providing continuous locomotion as well as efficient helping to perform daily activity of a patient with paralysis [13]. Moreover, this combination enables a reduction in the overall weight of the exoskeleton because smaller actuators can be used as the patient muscles help the movement and thus improves its portability. EMG may be monitored to assess muscle fatigue induced mainly by FES. This feedback is useful for the physiotherapists to evaluate the patient progress and to adapt the rehabilitation session. Other information can be extracted from the EMG signal such as intention or force estimations. Intention means the movement intention of the user. The intention is related with the activity of the muscle involved in the movement. This estimation may be used to trigger FES or the actuator. Force estimation gives an additional information about the size of the intended movement. Thus, this information can be used to adapt proportionally the actuator or FES assistance. Moreover, the exoskeleton should be easy to use for allowing at-home rehabilitation. The prototype exoskeleton is shown in Figure 1.1

Figure 1.1: Prototype upper-limb exoskeleton developed by Ashley Stewart

My goals in this project were to process the raw EMG signal coming from the EMG sensor developed by Benjamin Fortune. Firstly, intention estimation is performed: a binary value that indicates whether the person wants to move the muscle. Second, muscle activity estimation is evaluated: this is provided by a normalized value representing the size of the movement which the person wishes to perform. Normalisation requires measuring what the maximum EMG signal is for a particular person each time the sensor is used on a different person or at the start of a different session. Third, muscle fatigue assessment is done using the decrease of the mean and median frequency according to time. The tasks mentioned above should be achievable in conjunction with the use of FES on the same muscle and preferably during non-isometric contractions if possible (while the arm is moving). Some keys are given to analysis the EMG signal during simultaneous use of FES. Finally, a tentative to estimate the elbow angle using information coming from the EMG signal is done and analysed.

Approval from the University of Canterbury Human Ethics Committee was granted for testing the EMG sensor and the FES system.

Chapter 2

Background

This chapter reviews, firstly, the basis of the musculo-skeletal structure and its contraction mechanisms including the biological process and the neuronal control. Secondly, the source of surface electromyography signal is described. Finally, functional electrical stimulation is briefly explained.

2.1 Muscles

The human body consists of three kinds of muscles: cardiac, smooth and skeletal muscles. The latter are responsible for producing skeletal movement. Therefore, the focus is done on the comprehension of skeletal muscle structure and its contraction mechanisms.

Skeletal muscles are composed of a bundle of aligned axial muscle fibers. Each muscle fiber is a set of several myofibrils which consist of an assembly of thick and thin filaments. The thick filament is composed of myosins whereas the thin one is made up of two strands of actins, troponin and tropomyosin. The thin and thick filaments are perfectly arranged giving the striated appearance to the skeletal muscle. The muscle can be divided into small units called sarcomeres. The Z-lines separate each sarcomere and these lines are clearly visible on transmission electron microscopy (TEM). The sarcomere explains the sliding-filament model of muscle contraction. Figure 2.1 summarizes the structure of skeletal muscles.

Sliding-filament model and biological process of muscle contraction

The sliding-filament model stipulates that the sarcormere is the unit of the contraction. A detailed sarcomere schematic is summarized in Figure 2.2. In the sliding-filament model, the thick and thin filament lengths remain constant. Indeed, the contraction is due to sliding of the two filaments across each other. Muscle contraction can be explained based on sliding inside only one sarcomere.

The myosin head is the main actor of the contraction. This head contains two binding sites: actin and adenosine triphoasphate (ATP) binding sites. At rest, the myosin head is in its lower energy configuration, i.e. link with ATP. The myosin head cannot bind to the thin filament. During a contraction, hydrolisation of the ATP into adenosine diphosphate (ADP) and inorganic phosphate (P_i) occurs. The hydrolisation causes the myosin head to be in its higher energy configuration. The head is dressed up and the binding between the both filaments is now possible. Therefore, the myosin head links to the actin of the thin filament and the ADP and P_i are released. As a result, the myosin head takes its lower initial energy configuration again and the

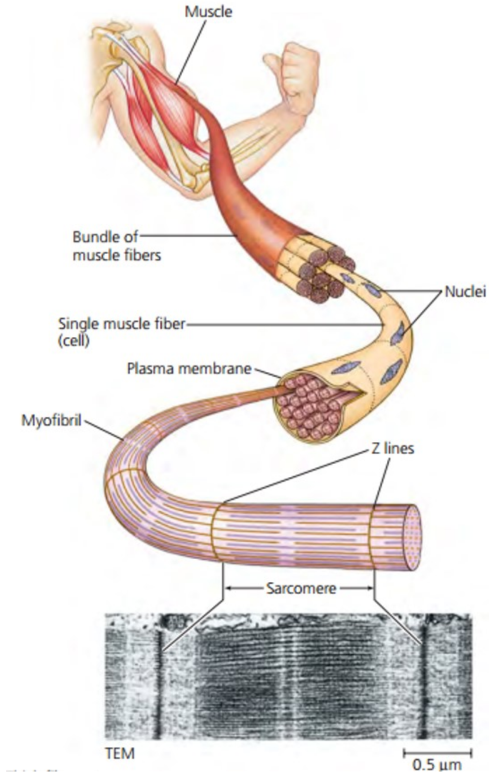


Figure 2.1: Skeletal muscle structure [1]

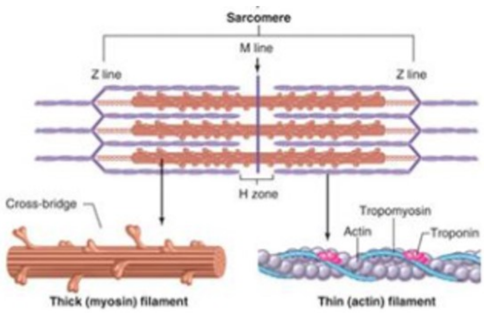


Figure 2.2: Sarcormere unit including detailed thick and thin filaments [2]

thin filament is driven towards the sarcomere center. The distance between the Z-lines decreases inducing the sarcomere contraction. The cross-bridge between both of the filaments is broken when a new ATP links the myosin head. A new cycle can begin again.

The muscle contraction cycle is only possible if the myosin binding sites of the thin filament are exposed. This exposition depends on regulatory proteins (tropomyosin and troponin) and on the calcium (Ca^2+) concentration in the cystosol. A muscle contraction is triggered by an action potential sent by a motor neuron. The neuronal control will be further explained. The action potential allows the Ca^{2+} release from the sarcoplasmic reticulum into the cystosol. The Ca^{2+} binds to the troponin. The configuration of the tropomyosin on the actin changes allowing the exposition of myosin binding sites: the muscle contraction occurs. When the action potential disappeared, the cytosolic Ca^{2+} is actively removed thanks to pumps into the sarcoplasmic reticulum. Therefore, cytosolic Ca^{2+} concentration decreases, the myosin binding sites are not accessible any more and the muscle relaxes.

Neuronal control of muscular contraction

Each muscle fiber is controlled by only one motor neuron. However, a motor neuron can manage several fibers. Therefore, the contraction of a particular muscle is controlled by many motor neurons and these neurons may be associated with quite a few fibers. In other words, a skeletal muscle consists of several motor units (MUs). MUs are composed of a motor neuron, its axons and its associated fibers. Figure 2.3 illustrates this decomposition of neuronal control. The number of muscle fibers, that means the innervation ratio, in each MU is variable. The more the muscle performs large movement or produces large force, the higher is the innervation ratio. For instance, the innervation ratio of the biceps brachial is approximatively 72 [3].

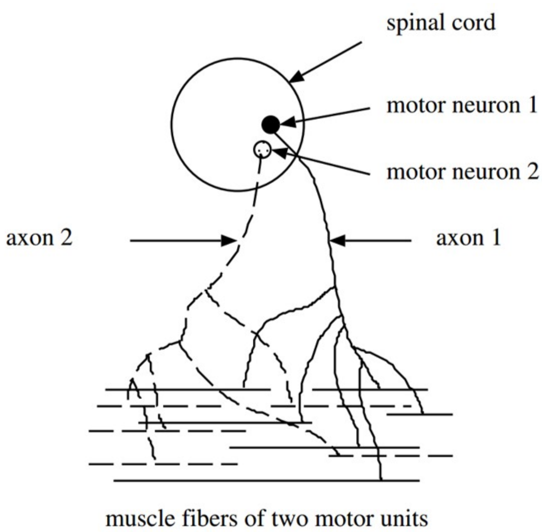
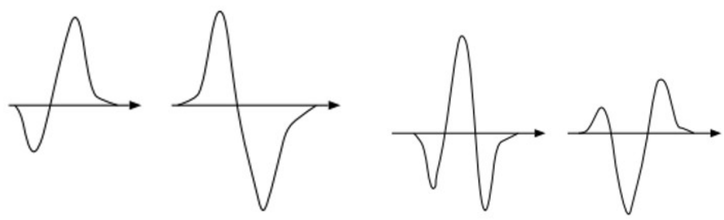


Figure 2.3: Two motor units : one represented in solid line and the other one in dashed line [3]

A neuron sends an action potential, called single-motor-unit action potential (SMUAP), through its axons towards its related fibers. This action potential induces a simultaneous "all or nothing" contraction of the overall MUs fibers. That means, the MU is the smallest unit which may be contracted. The SMUAP waveforms are usually biphasic or triphasic, illustrated by Figure 2.4, and last between 3 and 15 ms with a period of 6 to 30 s. Moreover, their amplitudes vary among 100 and 300 μV [3]. The summation of the SMUAPs gives the electromyography (EMG) signal. SMUAP shape provides an amount of information concerning the diagnosis of neuromuscular disorders [8]. The use of needle electrodes enables registration of SMUAPs.



(a) Biphasic waveform (b) Triphasic waveform

Figure 2.4: SMUAP waveforms [3]

The contraction of one fiber is brief and "all-or-nothing" type. However, the contraction force of a specific muscle can vary. Indeed, this graduation can be done via two ways: the number of fibers involved (spatial recruitment) and the stimulation frequency of fibers (temporal recruitment). Spatial recruitment means the contraction force increases according to the number of MUs implicated and their size. Temporal recruitment occurs when several action potentials are sent before the total fiber relaxation. This recruitment is illustrated by Figure 2.5. An unique action potential provides a brief contraction. If a second action potential is sent to the fiber before its total relaxation, the contraction force increases. The force can increase until the tetanic contraction: the fiber does not relax between the contiguous action potentials. The tetanic contraction is in fact a normal contraction that means a continuous contraction.

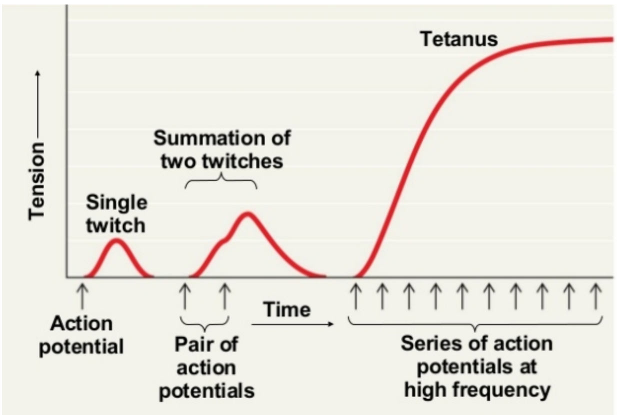


Figure 2.5: Temporal recruitment until tetanic contraction [1]

Type of contraction

A contraction can be classified into three different types which influence the EMG signal [5]:

- **Isometric contraction**
  The muscle length remains constant during an isometric contraction. For example, it happens when the muscle carries a load in a specific unchanging position.

- **Concentric contraction**
  A shortening of muscle occurs during the concentric contraction. The muscle can produce a movement, it exerts a force greater than the external resistance. The EMG signal amplitude is lower than in isometric contraction given that some energy is lost in the shortening processes.

- **Eccentric contraction**
  When the external force overcomes the force exerted by the muscle, the muscle stretches out, providing an eccentric contraction.

2.2 Electromyography Signal

The EMG signal can be recorded with needle electrodes or surface electrodes. If the EMG signal is recorded with surface electrodes, it is called surface EMG (sEMG) signal. Surface electrodes are preferred given that it is a non invasive method. Details concerning this subject will be developed later. However, the sEMG signal is complex. Indeed, surface electrodes register several SMUAPs and sometimes signals from different muscles. This phenomenon is called crosstalk and may induce some noise.

Figure 2.6 depicts the model of the generation of sEMG signal. The motor neuron firing pattern can be modeled as an impulse train. This activates and generates SMUAP. The summation of the SMUAPs gives the physiological sEMG signal $m_p(t, F)$ which is dependent on the time t and the force produced F. This is the physiological part of the model. The second part of the model concerns the recording instrumentation. As in all recordings, some noise $n(t)$ is induced. The different kinds of noises will be further explained. In order to attenuate these noise components, electrode and recording equipments have specific characteristics and perform some treatments $r(t)$. These will be explained in Chapter 3. Finally, the sEMG signal $m(t, F)$ may be visualized and further analysis can be performed.

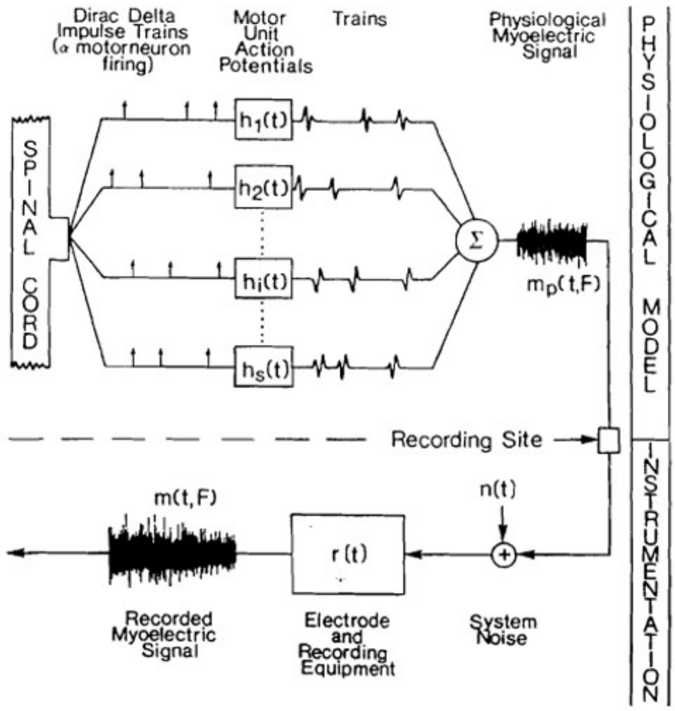


Figure 2.6: Model of the generation of sEMG signals [3]

Characteristics of sEMG signal are mentioned in Table 2.1. The amplitude of the signal is a stochastic process and a Gaussian distribution function can be used to represent it [9]. The amplitude reflects the number of MUs involved and the SMUAPs frequency in the muscle over a given period [14]. However, it is impossible to distinguish spatial from temporal recruitments.

Peak-to-peak amplitude	0 - 10 mV
RMS amplitude	0 - 1.5 mV
Frequency range	0 - 500 Hz
Dominant frequency range	50 - 150 Hz

Table 2.1: Characteristics of the sEMG signal[8] [9]

Noise

Several noise sources have to be take into account for the sEMG signal recording. There exist four major sources of noise [9] :

- **Inherent noise from the recording equipment**
  This noise can not be removed. The only solution is to use high quality components.

- **Ambient noise**
  Electromagnetic radiations (50 or 60 Hz and its harmonics) are everywhere and have a high impact on the sEMG signal given its small amplitude.

- **Motion artifacts**
  Motion artifacts include the relative movement between the electrodes and the skin and the movement of electrodes cables. The frequency contents of these artifacts are mostly comprised between 0 and 20 Hz [15].

- **Inherent instability of the signal**
  Instabilities of the sEMG signal are mainly present for the frequency contents range from 0 to 20 Hz. These instabilities are due to random characteristics of the MU firing rate. Therefore, in order to maintain signal stability, this frequency range should be removed from the sEMG signal.

2.3 Functional Electrical Stimulation

Functional electrical stimulation (FES) is a particular type of neuromuscular electrical stimulation (NMES). The purpose of FES is to accomplish functional tasks by activation of a single muscle or a group of muscles. This activation is performed using several electrodes which induce an electrical stimulation in a similar way to SMUAPs. Therefore, FES can be used to assist or replace voluntary movement of a stroke patient. To achieve this goal, specific stimulation sequences and magnitudes have to be defined. The electrode placement and stimulation characteristics used will be explained in Chapter 3.

Moreover, FES drives the neural repair of the stroke patient. Neural plasticity, which is brains ability to repair itself after an injury, has been proven to be quicker using the repetition of functional tasks than simple range-of-motion movement [12]. FES allows this high repetition even if patient movement is minimal.

Stimulation characteristics

In the most cases, the electrical stimulation is a symetrical biphasic waveform as shown in Figure 2.7. The main parameters that characterise the electrical stimulation are the following: pulse amplitude, pulse duration and stimulation frequency.

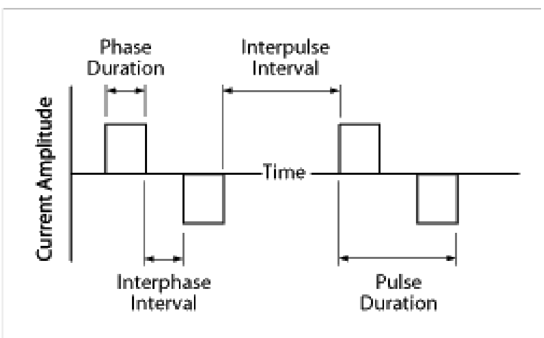


Figure 2.7: Symetrical biphasic waveform used for the FES © Medi-Stim

As in voluntary contraction, the contraction intensity is regulated using temporal and spatial summations. If the frequency of stimulation increases, the contraction force increases. Above a specific frequency, called fusion frequency, muscle fibers do not have time to reach their resting state. Thus, the contraction is continuous like the tetanic contraction in the case of voluntary contraction. Below the fusion frequency, fiber twitching occurs. It is important to know that with higher frequencies, more muscle fatigue occurs [16]. Hence, stimulation frequency used in FES is usually close to the fusion frequency. The number of fibers involved (spatial summation) in the contraction is related to the pulse duration and the amplitude stimulation [17]. If these stimulation characteristics provide an applied stimulus below the nerve fiber stimulation threshold, no action potential reaches the sarcoplasmic reticulum and no contraction occurs. If the pulse duration or/and the amplitude stimulation increases, the stimulation intensity increases as well hence the electrical field created enlarges and more fibers are involved in the contraction.

Characteristics of FES application for the upper limb are summarized in Table 2.2.

Minimum fusion frequency	12.5 Hz
Stimulation frequency range	12 - 16 Hz
Pulse duration range	0 - 300 μs

Table 2.2: Characteristics of FES therapy for the upper limb [10]

sEMG signal during FES

The sEMG signal is different when the contraction is due to an electrical stimulation as FES. The sEMG signal recorded during an stimulation is called a compound muscle action potential (CMAP) or more commonly M-wave. The electrical stimulation elicits synchronized SMUAPs in muscle fibers in the electrode vicinity [18]. The sum of this synchronized SMUAPs gives the M-wave. Therefore, the muscle response due to a electrical stimulation is a quasi-deterministic signal, given that contiguous M-waves are very similar [19]. However, in the most cases, there is a presence of stimulus artifacts (electrical signal/interference from the FES signal). These artifacts will be developed in more details in Chapter 4.

Figure 2.8 shows parameters which characterize the M-wave, including the stimulus artefact. $PosT$ is the time between the stimulus artifact and the positive peak, $PtpT$ is the peak to peak time, $PtpA$ is the maximum amplitude between the two peaks and $Area$ is the area of the two peaks.

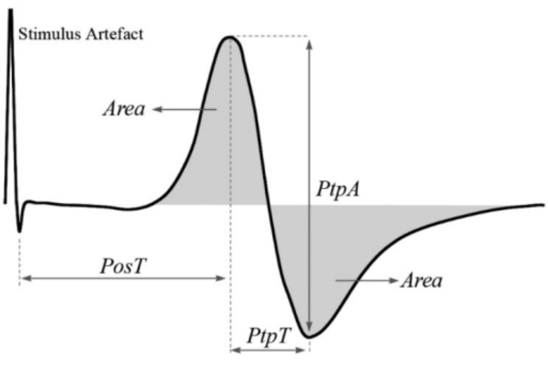


Figure 2.8: M wave and its parameters: $PosT$, $PtpT$, $PtpA$ and $Area$. The stimulus artefact is represented [4]

Studies have shown that electrical stimulation improves rehabilitation progress. Moreover, this one can be assessed with the characteristics of the maximum M-wave as its amplitude evolves according to the training duration.

Chapter 3

Data acquisition

How the data is recorded is explained in this chapter. This chapter contains two sections: hardware and software parts. The first section resumes which components are used to record the sEMG signal, to apply FES and to measure the elbow angle. The two software used (Arduino IDE and Matlab) during this project are briefly described in the second section.

Some processing using hardware and software are needed to record the sEMG signal. First of all, the electrical noise sources have to be removed such as the electromagnetic interference and the motion artifacts. These issues are overcome using special hardware components. Then, surface electrodes are necessary to capture the electrical muscle activity from the skin. A lot of time was consecrated to find electrodes providing satisfactory results. After that, another requirement for providing consistent data for further analysis is to have a precise sample frequency. This is performed using Arduino. Finally, the sEMG signal must be displayed in real time. The software Matlab is used to show the sEMG time evolution as well as other information such as intention, force and fatigue estimation.

3.1 Hardware

First, the necessary hardware to record sEMG signal can be divided into two main parts: Electronic sEMG circuit and the electrodes. The circuit design is briefly explained. Several electrodes are tested and characterized in order to find which kind is the most appropriate in our project. Second, the electronic FES circuit is outlined. Finally, another sensor is used during the project: angle sensor.

3.1.1 Electronic sEMG circuit

A sEMG circuit has been designed by Benjamin Fortune. This circuit costs approximatively \$30 ($\approx$ 20 €) which is cheap in contrast to the commercial ones. The circuit consists of two inputs and two outputs. The inputs are 'Electrode +' and 'Electrode -' and these ones allow to measure the muscular electrical activity. The first output is 'Reference Electrode' and it is used during the attenuation of electromagnetic interference (EMI). The second output is 'Output Signal' which is the signal of interest, that means this signal reflects the muscle activity after a specific signal processing. The electronic circuit can be divided into four major parts as shown in the block diagram in Figure 3.1:

- **Instrumentation amplifier**

The instrumentation amplifier is a differential amplifier using three electrodes ('Electrode +' and 'Electrode -' and 'Reference Electrode') and provides one output signal. The subtraction of the signals coming from the two input electrodes is taken. Therefore, the common signal in both signals is rejected. Then, the output signal is amplified with a fixed gain of 50 V/V.

This processing allows to reduce the crosstalk phenomenon.

- **Active band-pass filter**
  This filter removes frequencies below 20 Hz and above 480 Hz. The lower cutoff frequency is chosen in order to remove the movement artifacts between the electrodes and the patient whereas the higher cutoff frequency is selected to remove unwanted signals produced by the tissue at the electrode site.

  Moreover, the gain of the filter is adjustable. This is a great advantage as the sEMG amplitude varies according to the subject, the performed task, the moment of the day and the considered muscle. The gain filter range is 4.3 V/V to 104.3 V/V. The instrumentation amplifier has a fixed gain of 50 V/V, therefore the total gain may vary from 215 V/V to 5215 V/V.

  No notch filter is used to reduce the ambient noise (50 Hz). Indeed, an implementation of this filter will reduce the surrounding frequencies of 50 Hz as well. It can be a considerable issue given that the dominant frequency range of the sEMG signal is 50-150 Hz as said previously. Therefore, another technique called "Right leg driver" (RLD) is used to remove the power line interference.

- **Right leg driver**
  A RLD circuit is commonly utilised during the recording process of biomedical signals. This is due to the small amplitude of the signals compared to the high amount of coupled electromagnetic interference. The purpose of RLD is to attenuate the EMI. For that purpose, the common mode voltage is inverted, amplified and used to drive the subject's body through the 'Reference Electrode'.

- **Power and isolation**
  The circuit is supplied by 5V due to the system acquisition used (Arduino). In future, the circuit will be isolated to provide a subject safety if power supply leakage currents occur.

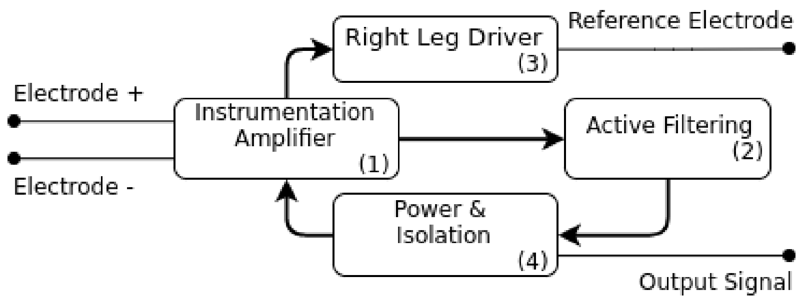


Figure 3.1: Block diagram of the sEMG circuit made by Benjamin Fortune

The circuit is made of two channels to provide the measurements of two muscles as illustrated in Figure 3.2.

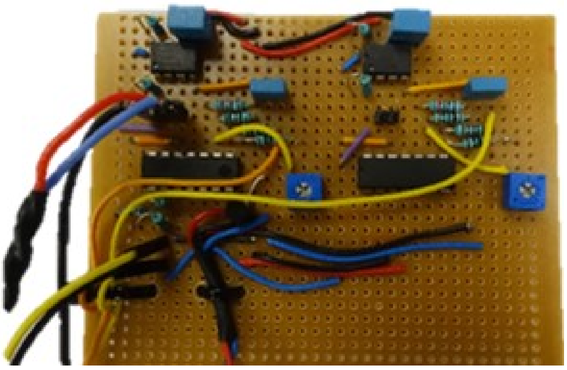


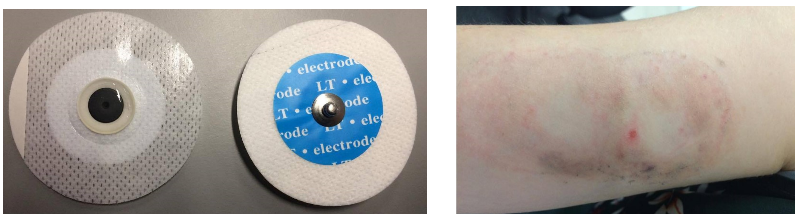
Figure 3.2: Prototype circuit board conceived by Benjamin Fortune

I contributed and I am an author on a paper [20] submitted and in review for a conference [1] about this sEMG circuit: "Design and Testing of a low-cost Electromyogram that Uses a Right Leg Driver Circuit".

3.1.2 Electrodes

The muscle activity can be measured using needle or surface electrodes. Needle electrodes are directly in contact with the muscle and thus the crosstalk noise is less present than with the surface electrodes [8]. Nevertheless, this kind of electrodes are invasive, hence surface electrodes are more suitable and most commonly used.

The first electrodes tested were electrocardiogram (ECG) specific electrodes given that the lab where the project was performed had a lot of these. These electrodes are surrounded by hydrogel as shown in Figure 3.3a. However, these electrodes may cause damage to the skin after several uses as shown in Figure 3.3b. Hence, other electrodes have to be obtained.



(a) Surface electrode with gel

(b) Skin irritation

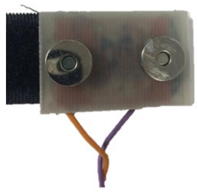
Figure 3.3: Surface electrodes with hydrogel

I designed the first electrodes. The latter are made of conductive fabric (silver-plated nylon). These ones consist of 2 disks of a diameter of 10 mm and spaced of 20 mm as recommended by the *SENIAM* (Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles) project [21]. The second ones are simply two nickel disks with the same geometrical characteristics as the fabric electrodes developed by Mervin Chandrapal during his thesis [22]. Nickel is chosen due to its high conductivity and its resistance to oxidation. These two kinds of surface electrodes are attached with velcro to allow their attachment to an arm bracelet (3.4c). A gel can be added to the nickel electrodes in order to increase the contact between the skin and the electrodes. *Spectra® 360* electrode gel manufactured by `Parker Laboratories` is used. This is a salt free

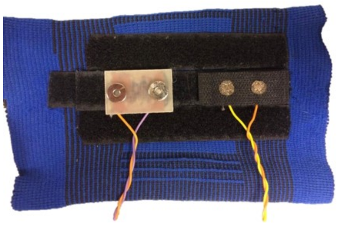
[1] http://www.m2vip-conference.org/

hypoallergenic gel.

(a) Surface electrode made of conductive fabric



(b) Surface metal electrodes



(c) Arm bracelet

Figure 3.4: The new electrodes developed

Finally, specific EMG electrodes are tested. These are a bipolar silver/silver chloride electrode called *Norotrode 20* manufactured by `Myotronics`. The inter electrode spacing is 22 mm and is similar to the other type of electrodes. Moreover, these electrodes are pre-gelled with hypoallergenic gel increasing the contact between skin and electrodes.

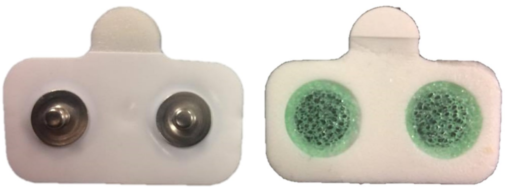
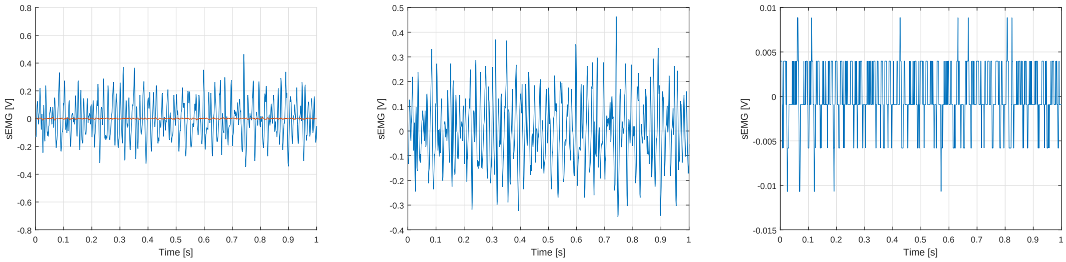


Figure 3.5: Norotrode - specific EMG electrodes

In order to evaluate the quality of the different electrodes, the SNR (signal-to-noise ratio) is computed. Delsys [23] recommended to measure the SNR value as follow for an sEMG signal:

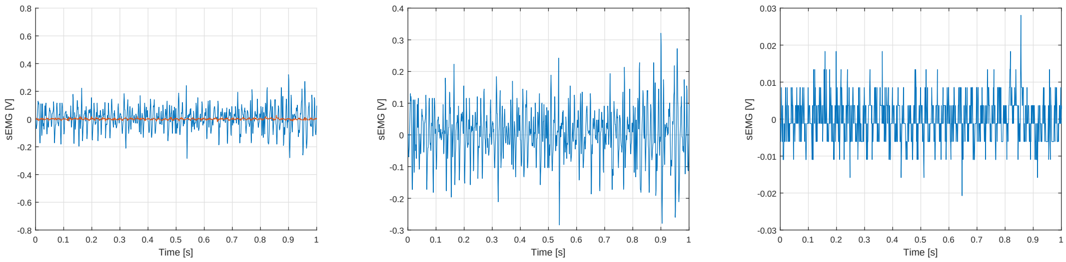
$$SNR = 20 \times \log \left(\frac{S_{RMS}}{N_{RMS}} \right) \text{ [dB]} \tag{3.1}$$

As the equation suggests, the SNR is the ratio of the RMS (root-mean-square) value of the signal of interest (S_{RMS}) and the noise (N_{RMS}). In our case, biceps activity is evaluated. The signal considered is a MVIC (maximal voluntary isometric contraction) [24] and the noise is recorded when the muscle is at rest. Obviously, the placement of the electrodes plays an important role and the position for every kind of electrodes is kept as consistent as possible. The gain of the sensor is at its smallest level. Figures 3.6, 3.7, 3.8 and 3.9 summarize these signals for the ECG, fabric, nickel and EMG electrodes respectively.



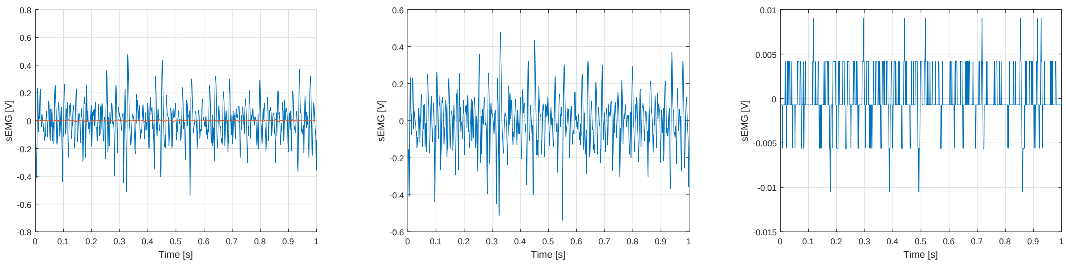
(a) Signal and noise (b) Signal (c) Noise

Figure 3.6: ECG electrodes



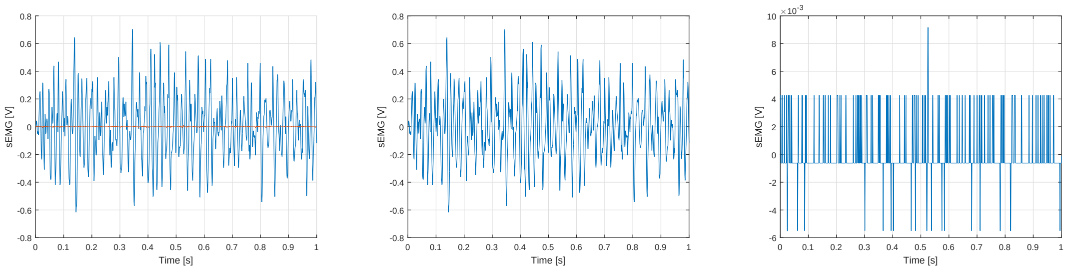
(a) Signal and noise (b) Signal (c) Noise

Figure 3.7: Fabric electrodes



(a) Signal and noise (b) Signal (c) Noise

Figure 3.8: Nickel electrodes



(a) Signal and noise (b) Signal (c) Noise

Figure 3.9: EMG electrodes

The set of SNR values are presented in Table 3.1. It is important to notice that for these measurements no skin preparation is used. The SNR values can probably be higher with addition of electrode gel and moreover if the skin is cleaned with alcohol and shaved.

ECG	**Fabric**	**Nickel**	**EMG**
31.90 dB	22.88 dB	33.13 dB	41.40 dB

Table 3.1: SNR values for the different electrodes

These SNR values are sensitive to a great number of factors. Thus, the SNR values are indicative and useful to direct the choice of adequate surface electrodes. During the measurements, fabric electrodes are noticed to be quite sensitive to the applied pressure to each on them. The addition of gel increases the contact between the skin and the electrodes and provide better results. However, its SNR value is still lower than the others. It could be explained due to a more important relative movement between the skin and the electrodes and a poor quality of skin contact as well. The position of electrodes has a significant influence on the SNR value. Difference between the SNR values could also be explained by the inaccuracy to keep the same electrode position.

Table 3.2 summarizes the advantages and disadvantages of these four kinds of surface electrodes.

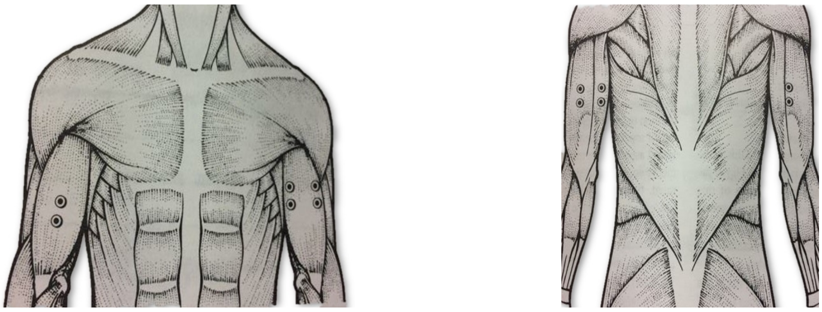
	Advantages	**Disadvantages**
ECG	* Sticky patch - Small relative movement of the electrodes * Already pre-gel	* Several electrodes do not work at all * No pair - difficulties to have the same inter spacing between uses * Skin irritation * Single use - price
Fabric	* Several use - price * Electrode array easily imaginable * Electrode pair	* High relative movement of the electrodes * Poor skin contact * Lowest SNR value * Arm bracelet needed
Nickel	* Several use - price * Electrode pair	* High relative movement of the electrodes * Arm bracelet needed
EMG	* Sticky patch - Small relative movement of the electrodes * Already pre-gel * Electrode pair * Highest SNR value	* Single use - price

Table 3.2: Comparison of the different surface electrodes tested

Therefore, for the rest of the measurement the EMG electrodes are chosen due to their advantages. For the future, reusable surface electrodes are suitable. The conductive fabric electrodes seem promising. Indeed, our fabric electrodes are handmade and attached to velcro tape in order to choose the spot of the recording. Velcro tape can induce relative movement which can be a problem. Conductive fabric directly sewn on cloth will lead to best results. Moreover, the arm bracelet used was too stretched out reducing the skin-electrode contact. Electrode arrays are easily conceivable using conductive fabric allowing the recording of several muscles.

Placement of the electrodes

The electrode placement is a key factor to obtain a signal with sufficient quality. As said before, with the surface electrodes, the activity of muscles in the vicinity of the muscle of interest may be recorded. This phenomenon is called crosstalk and may be reduced if the electrodes are placed in the middle of the muscle belly [25]. The surface electrodes have to be placed according to the fiber length. The recommended electrode positions for the biceps and the triceps are illustrated on Figure 3.10.



(a) Biceps (b) Triceps

Figure 3.10: Recommended position of the electrodes [5]

3.1.3 Electronic FES circuit

Lachlan McKenzie, the Ph.D. student responsible for the FES, has developed an electronic FES circuit. He uses a symetrical biphasic waveform for the electrical stimulation as illustrated by Figure 2.7. The current amplitude is a constant ± 20 mA. The phase duration is typically between 0 and 600 μs and the stimulation frequency typically ranges from 20 to 50 Hz. With these frequency and phase duration variables, the contraction force can be controlled. If the stimulation is too weak, no contraction occurs at all. The stimulation intensity necessary to trigger a contraction depends on among other things on the subject, the stimulated muscle and the electrode.

Electrical stimulation is sent through electrodes. The configuration used is bipolar electrodes. One is the active electrode which is placed in the vicinity of the muscle of interest. The second one is the indifferent electrode and it is located close to the active one.

For illustration, the circuit is shown in Figure 3.11.

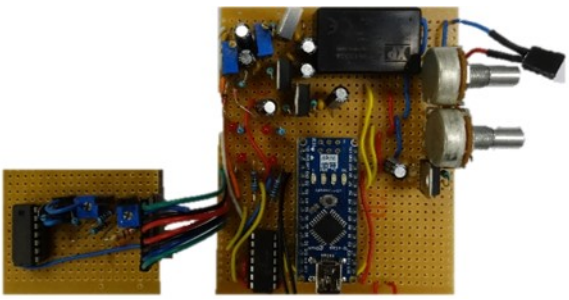


Figure 3.11: FES circuit designed by Lachlan McKenzie

3.1.4 Other sensor

Another sensor is used in this project in order to record the elbow angle. This value is necessary in order to link the sEMG signal from the biceps to the elbow angle. The elbow angle estimation is treated in Chapter 8.

Exoskeleton combined with a potentiometer

In Chapter 8, the elbow angle has to be evaluated. Ashley Stewart developed a prototype exoskeleton equipped with a potentiometer which can measure the elbow angle as illustrated in Figure 3.12. The exoskeleton is putted on the arm which elbow angle has to be recorded. The rotary potentiometer turns according to the elbow angle. Thus, the variable resistor inside evolves according the angle providing an output signal related to the angle. However, during its use, it is noticed that it is not comfortable for the subject and the measure is not performed with a high accuracy. The velcro tape hurts the user and does not allow a total flexion/extension movement. Hence the choice of another sensor has to be considered.

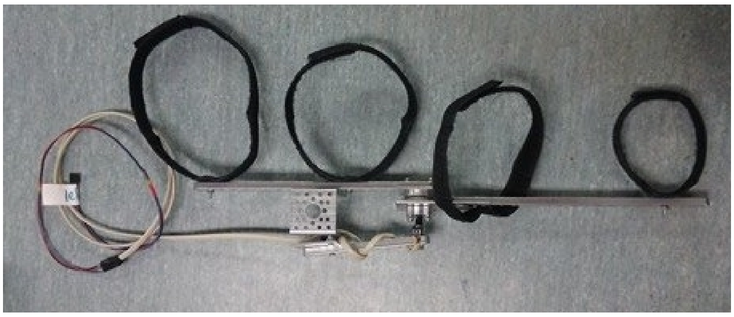


Figure 3.12: Angle sensor - Exoskeleton combined with a potentiometer

3.2 Software

Two software languages are used during this project. The first one is Arduino IDE and allows to record data from different sensors. The second one is Matlab and is used to process the data recorded by the Arduino. Processing could have been done using Arduino but Matlab is easier to handle.

In order to avoid aliasing, the Nyquist sampling theorem is applied to find the adequate sampling frequency f_s:

$$f_s \geq f_c \tag{3.2}$$

f_c is the highest frequency founded in the signal, that means 500 Hz. Therefore, a sampling frequency of 1000 Hz is enough to record the sEMG signal.

3.2.1 Arduino acquisition

The board used for this project is the Arduino MEGA 2560 connected on a PC USB port (Figure 3.13). After several trials to avoid problems due to the time constraint, the best solution found is the use of interrupts. 'Timer1' library of Arduino is used due to its simplicity of use. The interrupt mechanism enables a precise sample frequency. As previously explained, a sample frequency of 1000 Hz is sufficient to record the sEMG signal. Therefore, interrupts occur every 1 ms in order to record new sensor values (elbow angle and sEMG). Two distinct buffers are used. These ones consist of an array of 2 x 50 elements. The number 2 is used because two sensor values may be recorded whereas the number 50 is chosen as it does not exceed the buffer limitation. This working approach can be used to record more than two sensors at the same time.

Figure 3.13: Arduino MEGA 2560

The main loop of the code consists to print data of the actual buffer to the serial when it is full so it can be read by the PC running Matlab (R2016a). However, this printing can take more than 1 ms, so new sensor values should be recorded. It is on this case that interrupts play a great role and the second buffer as well. Therefore, the printing to the serial is stopped and the sensor values are recorded on the second buffer. After the recording, the printing continues until the end of the first buffer. Then, we wait till the second buffer is full and so on. As the data is sent to Matlab in the form of a bundle, the communication with Matlab occurs every 50×1 ms $= 50$ ms but the sample frequency remains 1000 Hz.

3.2.2 Matlab acquisition

Matlab is used to process the sEMG signal all along this project. Matlab receives data from Arduino in bundle form. The data transfer is performed using two main functions :

- `serial ('port', 'baudrate', 115200)` : this function creates a serial port object and allows the communication with the Arduino board (connected at port specified by the 'port' parameter) using a baudrate of 115200.

- `fscanf('fileID', 'format')`: this function reads the data from text file. The format used is '%s' meaning character string given that every sensor data sent by Arduino to Matlab is separated using a comma. Thus, the `str2num` function is used to remove the comma and a vector with the sEMG amplitude value is returned every 50 ms.

Thanks to Matlab, the raw sEMG signal is shown in real-time. Moreover, after some processing which will be further explained, intention, force and fatigue estimations may be displayed in real-time as well. In Chapter 8, Matlab processing is useful to determine the elbow angle.

Chapter 4

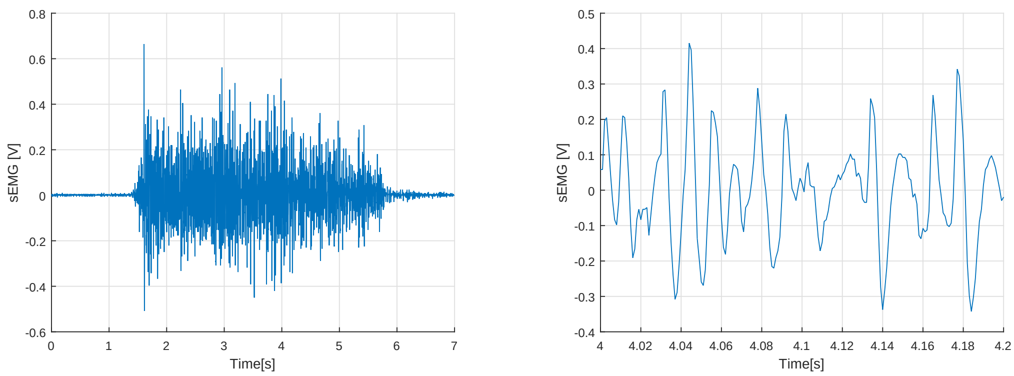
Data Analysis

This chapter consists of two parts. Analysis of the sEMG signal is summarized in the first one: envelope extraction to evaluate the muscle activity is investigated. The second part focuses on the sEMG signal during FES application. One method is explained to remove artifacts in the sEMG signal due to stimulation.

The sEMG signal is random in nature. A simple analysis of its time evolution does not give useful information. It is necessary to find a way to characterize the signal. Several mathematical formula have to be applied to the signal in order to reflect the muscle activity according to time. Concerning the sEMG in presence in FES, the signal is different: the SMUAPs are synchronized and their sum gives the M-wave. The M-wave analysis could be performed without a mathematical processing. Nevertheless, the application of the stimulation induces a high amplitude artifact. The latter has to be removed for further analysis. Indeed, the artifact alters the M-wave and its frequency spectrum. Thus, for example, fatigue estimation may be not properly evaluated without the stimulation artifact removal.

4.1 sEMG signal

The muscle contraction increases as more fibers are activated and the firing rate increases. As a result, SMUAPs begin to overlap. Thus, the sEMG is more and more complex. An example of sEMG signal recorded by the developed sensor is shown on Figure 4.1.



(a) sEMG signal (b) Zoom

Figure 4.1: sEMG signal example

Similar to most biomedical signals, sEMG signal is non-stationary which means that signal statistical characteristics change according to time. Non-stationarities can be classified into slow and fast stationarities. Metabolite accumulation results in slow non-stationarities. This accumulation is usually related to muscle fatigue. Fast non-stationarities are due to change in muscle length, force or/and electrode position [15]. sEMG signal can not be a stationary signal even if no movement is performed due to the inherent organ physiology [8]. Thus, the analysis of the sEMG signal has to be performed using short time analysis, during a short time duration, 0.5 - 2 s [19], the sEMG signal can be assumed to be quasi-stationary. However, during no isometric contraction, stationary hypothesis is not satisfied anymore. Therefore, dynamic contraction is more difficult to analyse. Hence, for first approximation, most of analysis in this work will be performed during isometric contraction.

Given the non-stationarities, a global analysis of sEMG signal is incoherent and short-time analysis has to be used. A periodogram of a part of a sEMG signal during a biceps contraction is shown in Figure 4.2. A periodogram is an estimation of the power spectral density of the signal. This PSD estimation is evaluated over a fixed window of 1 s.

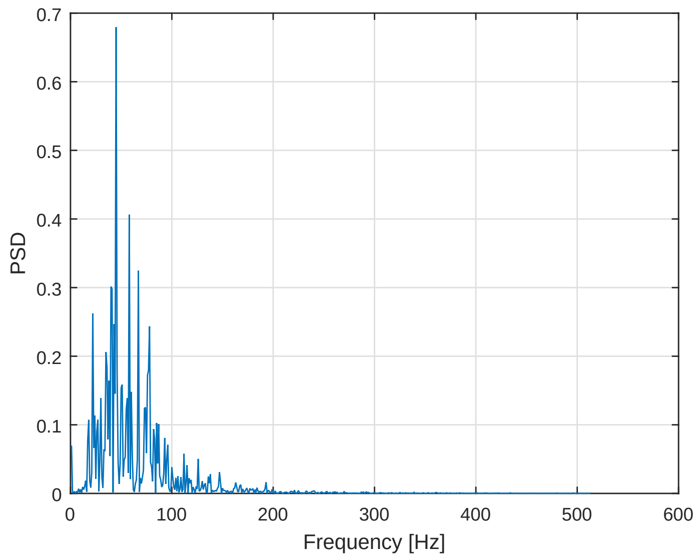


Figure 4.2: Periodogram evaluated of sEMG signal over a window of 1 s

The visual analysis is usually not possible, in contrast to electrocardiography (ECG) signal, except just for the trend of increase or decrease of activity level. Some methods have been defined to allow precise activity analysis in order to link electrical muscle activity to mechanical activity.

The measure of activity can be performed using several techniques [3]:

- **Zero-crossing rate (ZCR)**
  ZCR increases by one each time the signal crosses the zero-line or another reference. This measure is done on a specific window. Thus, it is a frequency indication. The more muscle activity occurring, the more signal spectrum moves to the right and ZCR increases. However, ZCR is highly influenced by noise.

- **Turn count (TC)**
  A turn is counted every time the sEMG slope sign changes. However, the difference between the signal slope change has to be higher than a specified threshold to avoid taking into account the sEMG signal variations induced by noise.

- **Root-mean square (RMS) value**
  Given that the sEMG signal is not stationary, the RMS value has to be evaluated over a specific window of M samples. The window length M is a key factor. The short-time RMS value is defined as follow:

$$\text{RMS } (t) = \left(\frac{1}{M} \sum_{k=0}^{M-1} x^2(t-k) \right)^{\frac{1}{2}} \tag{4.1}$$

- **Butterworth filter**
  The absolute value of the sEMG signal is taken (full wave rectification). Thus, high frequency-peaks are created due to this rectification: a lowpass filter has to be applied. The envelop can be obtained thanks a *Butterworth* lowpass filter. The order N and the cutoff frequency f_c of the filter depends on the raw signal. For the sEMG signal, $N = 8$ and $f_c = 8$ Hz provides a good trade-off between smoothing and reflecting the non-stationarity of the signal.

- **Moving average (MA) filter**
  Another method to extract the envelope is a moving average (MA) filter. With this method, a time average envelope $y(t)$ of a signal $x(t)$ may be expressed with this simple equation:

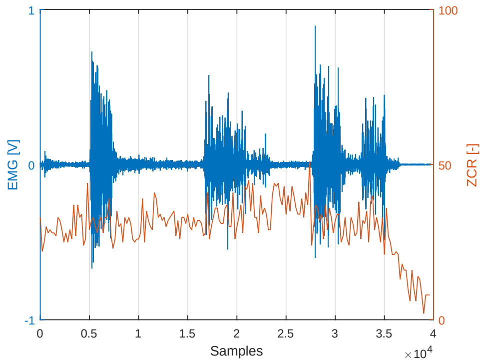
$$y(t) = \frac{1}{T_a} \int_{t-T_a}^{t} \mid x(t) \mid dt \tag{4.2}$$

  T_a is the duration of the MA filtering window.

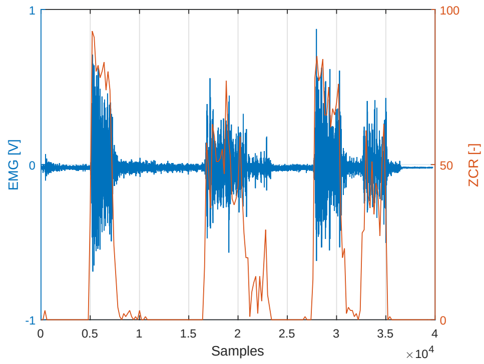
In all of these activity estimation techniques a window is used (except for the butterworth filter; N and f_c play the role of the window). The length of this window has to be chosen to the smooth of the discontinuities of the rectified signal but also to the importance to represent accurately the change in the sEMG signal amplitude wanted. Moreover, two kind of windows can be used: with or without overlap. Windows with overlaps are more precise but the computational time is higher. This is important for real-time analysis, particularly when using low-cost embedded systems such as Arduino.

These activity estimation techniques are applied to four isometric contractions of the biceps. This position is maintained during the entire experiment. This recording was approved by the Human Ethics Committee, University of Canterbury (HEC 2015/53/LR-PS) as the other recordings of this chapter. A non overlapping window of 200 samples is chosen for the all methods and the butterworth filter is characterized by $N = 8$ and $f_c = 8Hz$ as recommended by [3]. All the results are shown in Figure 4.3. First, ZCR is evaluated with the zero-line reference. This does not provide good results. Another reference is used: 0.02 V. Better results are obtained. It has been demonstrated that the noise level and the baseline of the sEMG signal alter this estimation approach. The threshold has to be chosen according to these factors. Third, TC is evaluated without a specific threshold: when any slope change occurs, TC is increased by one. The muscle activity is not well reflected due to the noise as expected. A constraint is added for the estimation: the signal slope change has to be higher than 0.02 V. By now, the value reflects the muscle activity. Fourth, the envelope extraction using a Butterworth filter provides good results as well as the estimation using a MA filter.

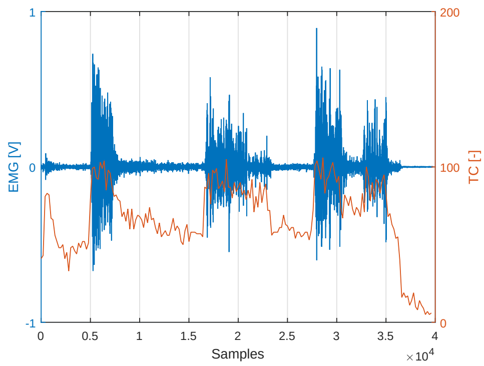
In conclusion, the RMS value is chosen to evaluate the muscle activity. First, this one is less sensitive to the noise level than ZCR and TC. Second, for real-time constraints, the RMS value is preferred over the estimation using the Butterworth filter. Finally, the RMS value and MA filter provide similar results but most of studies used the RMS value to assess muscle activity [3], [9]. Hence, the RMS value is used during this report mainly in Chapter 5 and 6.



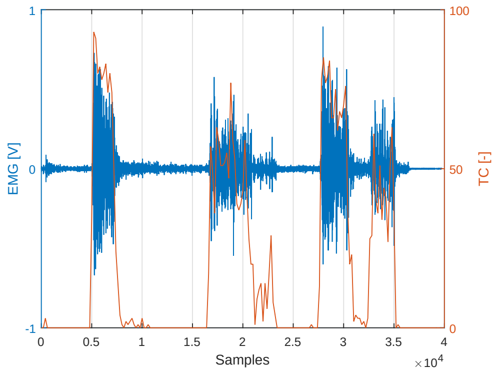
(a) ZCR with zero-line as reference



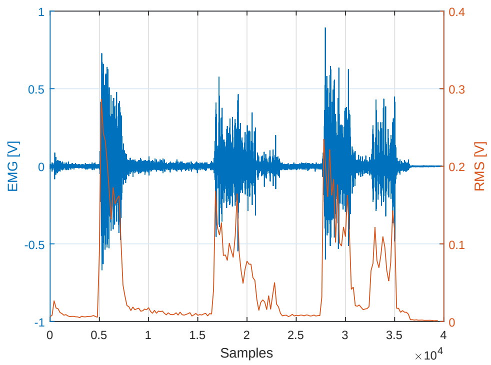
(b) ZCR with 0.02 V as reference



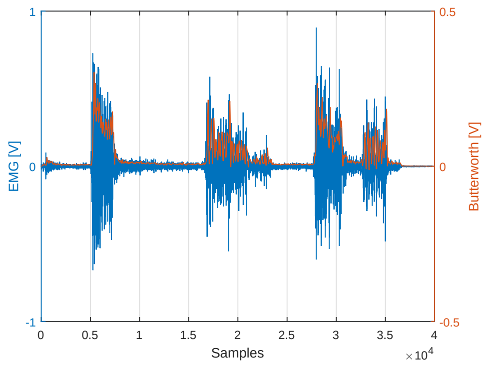
(c) TC with every slope change counted



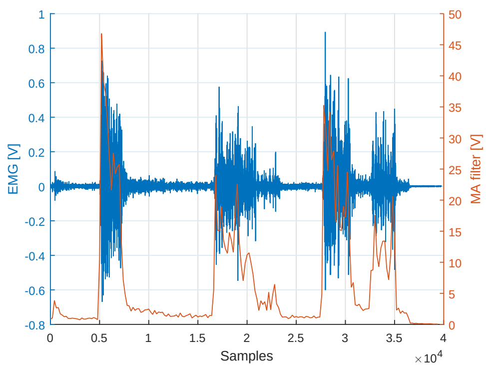
(d) TC with slope change higher than 0.02V



(e) RMS value



(f) Butterworth filter



(g) MA filter

Figure 4.3: Muscle activity estimation techniques

Other features can be extracted from sEMG to provide information about muscle activity or fatigue. These one are classified into time and frequency domains:

- Time domain : mean absolute value (MAV), mean value (M), Willison amplitude (WAMP), harmonic mean (HM), variance (VAR) and waveform length (WL)

- Frequency domain: autoregressive model coefficient (a_i), mean power frequency (MF) and median power frequency (MDF)

This set of features will be explained and used during the determination of muscle fatigue or elbow angle in Chapter 7 and Chapter 8 respectively.

The muscle activity can be studied using the analysis of SMUAPs as well. The sEMG signal decomposition into SMUAPs can be performed using wavelet transform technique. The SMUAPs analysis is useful to diagnose myopathy or neuropathy [3].

4.2 FES

In this research, FES is applied on the biceps and sEMG signal is recorded on the same muscle with a sample frequency of 1000 Hz using Arduino and Matlab. Moreover, elbow angle is recorded in order to evaluate if there is a movement. As demonstrated in Figure 4.4, when the amplitude of the FES exceeds a specific value (which depends on physiological parameters), the muscle contracts and a movement is performed.

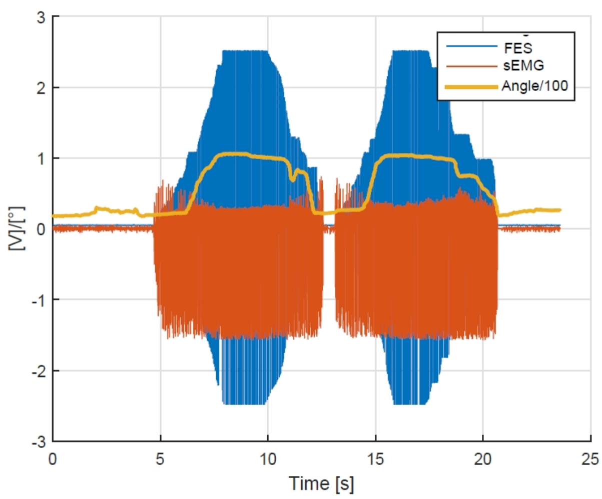
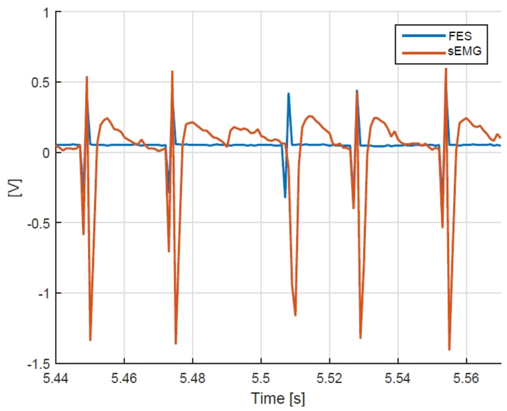
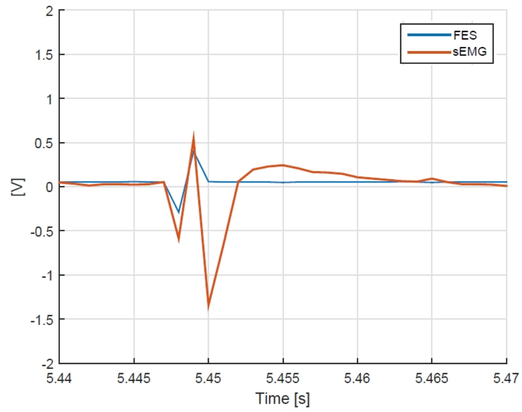


Figure 4.4: FES application, sEMG signal and elbow angle recording

Figure 4.5 depicts the sEMG signal when FES is not enough to trigger a movement. As Figure 4.5b shows, a stimulus artifact is well present. The impact of the contamination depends on the muscle studied as well as the electrical stimulation characteristics. M-wave spectrum is affected by this high frequency artifact and thus moves the M-wave spectrum to higher values [6]. It is important to notice that the sEMG signal amplitude is much lower than the stimulation artifact. The latter has to be removed in order to analyse the real sEMG signal in a coherent way.

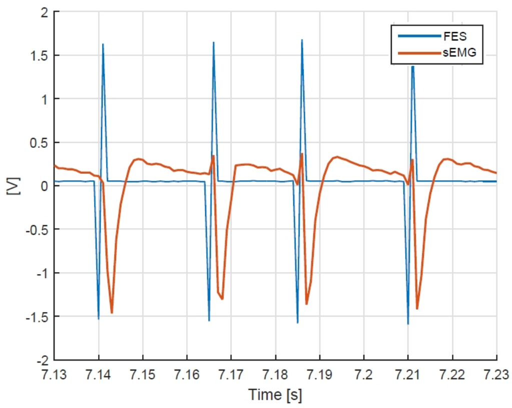


(a) Stimulation train and the corresponding sEMG

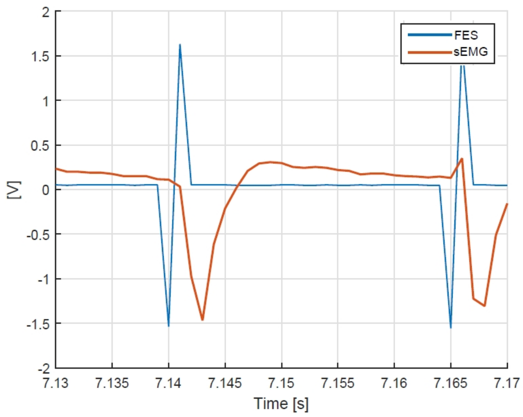


(b) M-wave

Figure 4.5: sEMG signal when the FES amplitude is too low to trigger a movement



(a) Stimulation train and corresponding sEMG



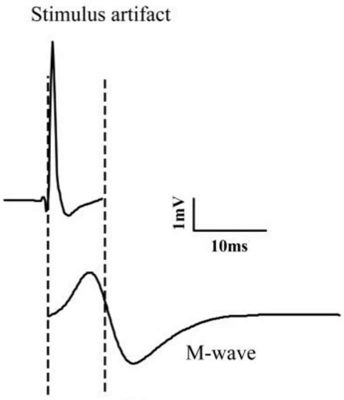
(b) M-wave

Figure 4.6: sEMG signal when the FES amplitude causing a movement

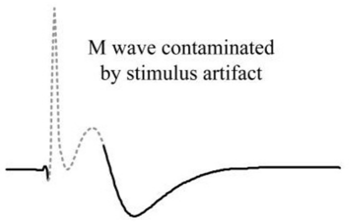
4.2.1 Suppression of stimulus artifacts

In the most cases of sEMG recording during FES, a stimulus artifact is present and has to be suppressed. M-wave and the stimulus artifact are illustrated in Figure 4.7a and the contamination by the artifact on M-wave is shown in Figure 4.7b. It can be seen that the artifact amplitude is lower than the sEMG signal which is the signal of interest. The amplitude difference could reach four orders of magnitude.

In order to remove the stimulation articfacts, a peak detection is performed using the `findpeaks` function provided by Matlab. A minimum peak height is specified as 0.4 V. The detection is not performed in real-time. As shown by Figure 4.8a, the stimulation peaks are correctly identified. Then, a stimulation period has to be defined in order to reconstruct the M-wave by piecewise cubic Hermite polynomials interpolation like done in the work of Liu et al. [6]. The period begins 4 samples before the detected stimulation peak and ends 5 samples after the peak. Thus, the stimulation artifact is assumed to last 10 ms. All stimulation periods are removed from the signal. Finally, a piecewise cubic Hermite polynomials interpolation is performed using the `pchip` function to recreate the M-wave.



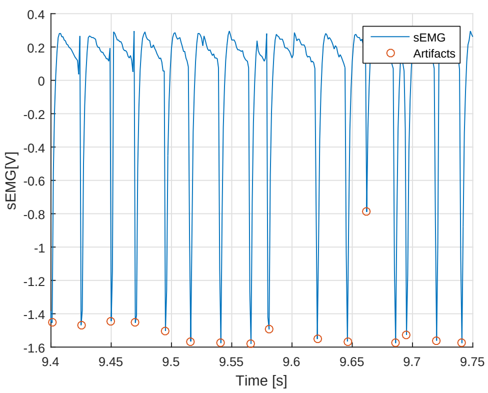
(a) M wave and stimulus artic-fact



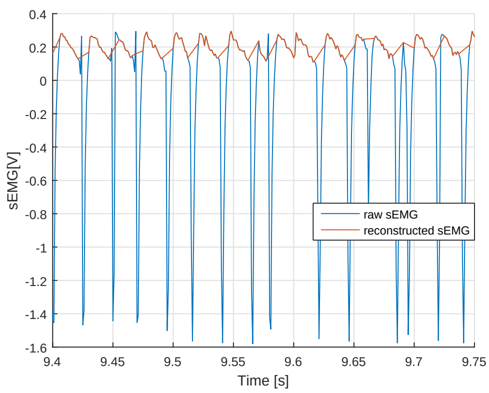
(b) M wave contaminated by stimulus artifact

Figure 4.7: Contamination M wave by stimulation artifact [6]

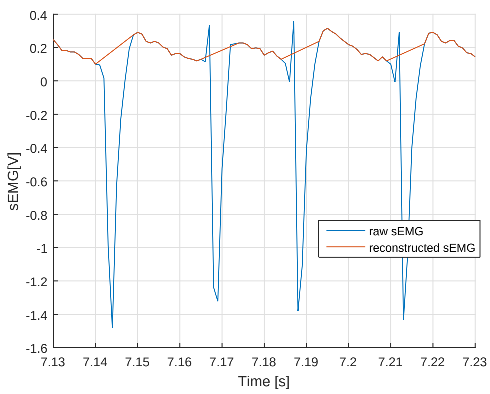
Reconstruted M-waves are illustrated in Figure 4.8b. Figure 4.8c illustrates the reconstruction of the M-waves contaminated by artifacts whose triggered a movement represented in Figure 4.6a.



(a) Stimulation peak detection



(b) Reconstructed M-waves



(c) Zoom

Figure 4.8: Suppression of stimulus artifacts

The sEMG signal recording in presence of FES was performed only once. At this moment, my knowledge in this area is limited. Hence, I can not draw a conclusion on this suppression of artifacts. Further analysis and research need to be performed. Indeed, thanks to a high-quality reconstruction of the M-wave, useful data may be extracted such as the fatigue of the stimulated muscle.

There also exist hardware methods to eliminate the stimulus artifact [26] [27].

Chapter 5

Intention estimation

In the first section, intention is evaluated without FES. First, given the complexity of sEMG signal, the RMS value is calculated using a specific fixed window to estimate the muscle activity. Second, a threshold is chosen to determine if a contraction occurs or not. Finally, a performance test is performed. The second section gives useful directions for intention estimation when FES is applied. The last part deals with the application of intention estimation without and with FES application in stroke rehabilitation.

Subject's intention is defined as his/her intention to perform a movement. The muscle becomes active as the subject wants to move. Thus, the intention estimation allows to find the on-off time of a specific muscle.

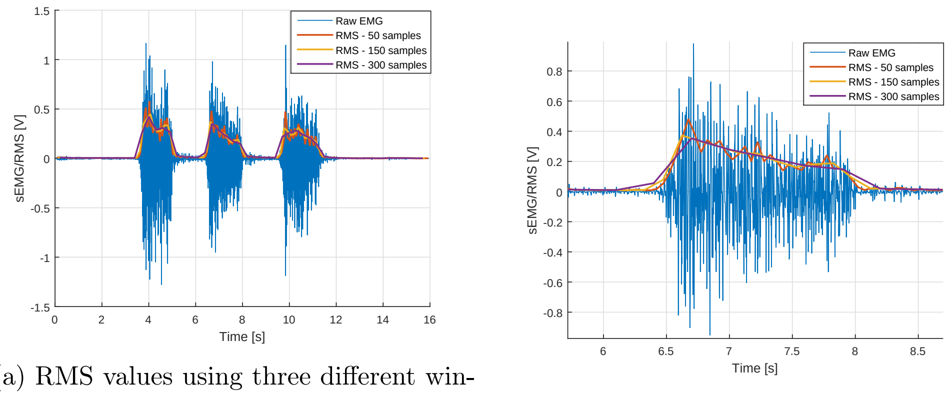
5.1 Intention without FES

In intention estimation, the assumption of isometric muscle is not necessary. Indeed, if the muscle activity is higher than a determined threshold, the muscle involves a contraction. As the project is about the upper limb, the biceps is the muscle of interest and all the experiments are performed on this muscle. This intention estimation method could be the same for other muscles.

Given that the intention is recorded in real-time, no overlapping is taken into account. Therefore, RMS value of one sEMG segment of N samples is given by:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{5.1}$$

Firstly, the RMS value is evaluated using different windows lengths: 50, 150 and 300 samples corresponding to 50 ms, 150 ms and 300 ms. The experiment was conducted by performing three dynamic contractions. This study was approved by the Human Ethics Committee, University of Canterbury (HEC 2015/53/LR-PS). Figure 5.1 shows the impact of the window length. The larger the window, the smoother the output signal. However, as demonstrated by Figure 5.1b, a large window introduces a delay, that means that the beginning of muscle activity is not well evaluated: the muscle dynamics are biased. This is important as the intention according to time has to be recorded. A small window introduces a great amount of variations: no effective averaging. Taking these observations into account, a window length of 150 samples is chosen.



(a) RMS values using three different windows length

(b) Zoom

Figure 5.1: Illustration of the different window sizes for the RMS evaluation

To estimate the on-off time of the muscle, in other words if there is a contraction or not, a threshold has to be defined. This threshold depends on the subject, the recording, noise and on the activity estimation methods.

Detailed observations of Figure 5.1b provide information concerning the choice of the threshold. After some trials, a threshold $T = 0.02$ V was chosen. If the RMS value exceeds this threshold during 150 ms, the muscle is considered as active. If the noise is higher, the threshold has to be increased. That means that the threshold is also dependent of the gain of the sEMG sensor.

Figure 5.2 depicts the raw sEMG signal, the RMS value using a window of 150 samples and the movement intention. The number 0 means no movement whereas the number 1 indicates a movement. As demonstrated by the figure, the movement is correctly determined.

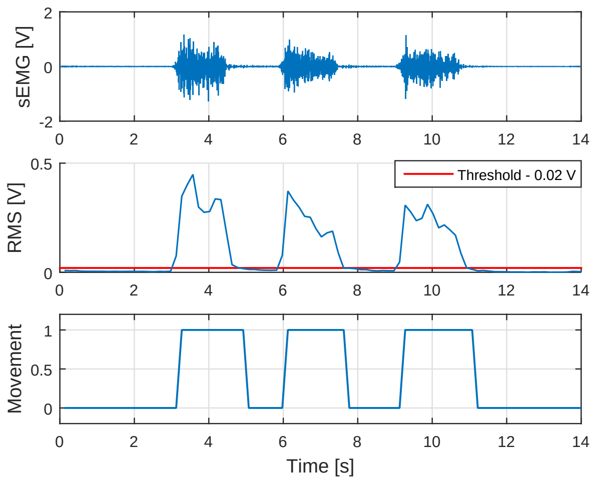


Figure 5.2: Movement evaluation

In order to evaluate the performance of this classification method, a performance test is done: 39 contractions are performed. All type of contractions are considered: isometric (sustained and brief) and dynamic contractions. These ones are represented in Figure 5.3.

Method performance may be evaluated using a confusion matrix shown in Table 5.1. True positive means that the contraction is correctly determined whereas false negative indicates a non detection of the contraction. When the muscle is at rest and a contraction is detected, this is called a false positive. True negative means that no muscle activity is detected when the muscle is at rest. The true positive classification was performed by an observer looking at the plot displayed in real-time.

	Predicted Class	
Actual Class	**Positive**	**Negative**
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

Table 5.1: Confusion matrix

Moreover, a classification method may be assessed using these three following characteristics:

- **Sensitivity** - accuracy of contraction detection

$$\text{Sensitivity} = S^{+} \quad = \quad \frac{TP}{TP + FN} \tag{5.2}$$

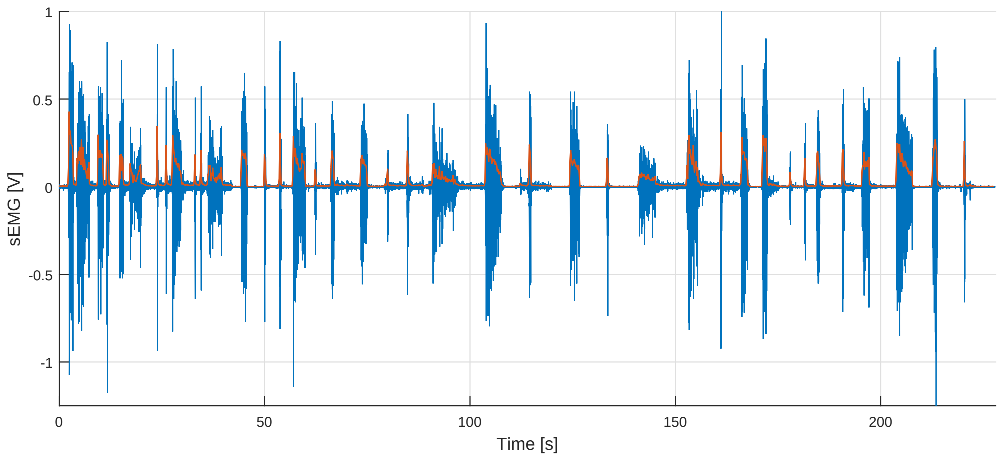
- **Specificity** - correctness to detect no contraction

$$\text{Specificity} = S^{-} \quad = \quad \frac{TN}{FP + TN} \tag{5.3}$$

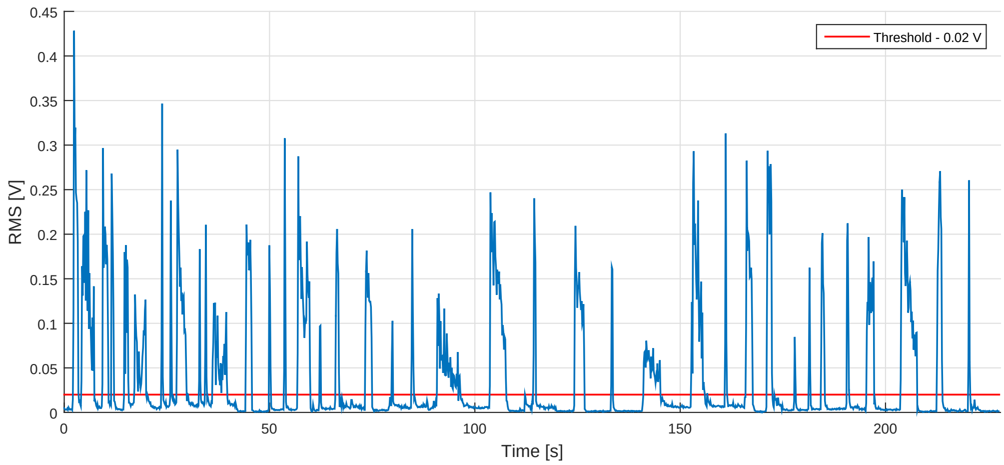
- **Accuracy** - overall precision

$$\text{Accuracy} \quad = \quad \frac{TP + TN}{TP + FN + FP + TN} \tag{5.4}$$

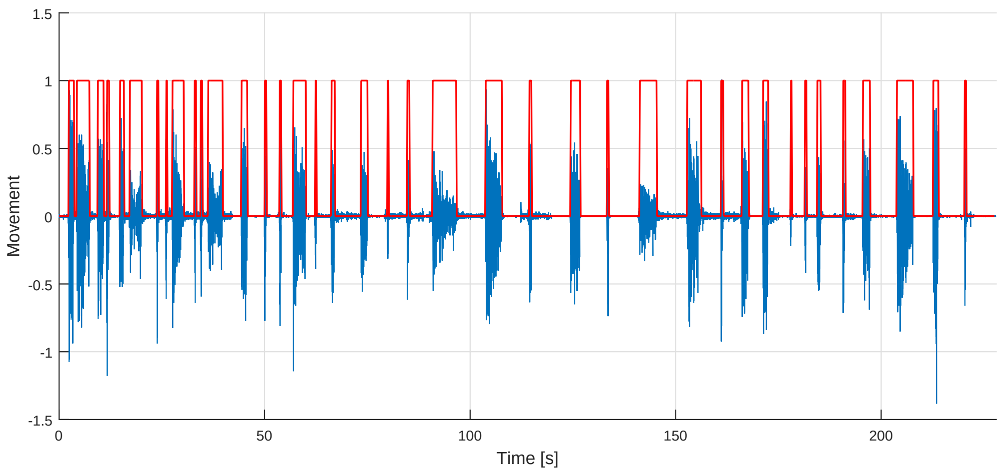
Figure 5.3 shows the train of contractions with its correspondent RMS value and movement intention estimation for a threshold $T = 0.02$ V. As seen on the set of graphs, the movement estimation seems correctly assessed. Table 5.2 proves this prediction. Indeed, the accuracy of the classification method is 100 %. All contractions are detected. Moreover, the contraction duration estimation is acceptable: not too short, not too high.



(a) sEMG and its RMS value using 150 samples



(b) RMS value using 150 samples and the threshold chosen $T = 0.02$ V



(c) Movement classification (1 = move and 0 = no move)

Figure 5.3: Set of 39 different contractions

Actual Class	Predicted Class: Positive	Negative
Positive	39	0
Negative	0	40

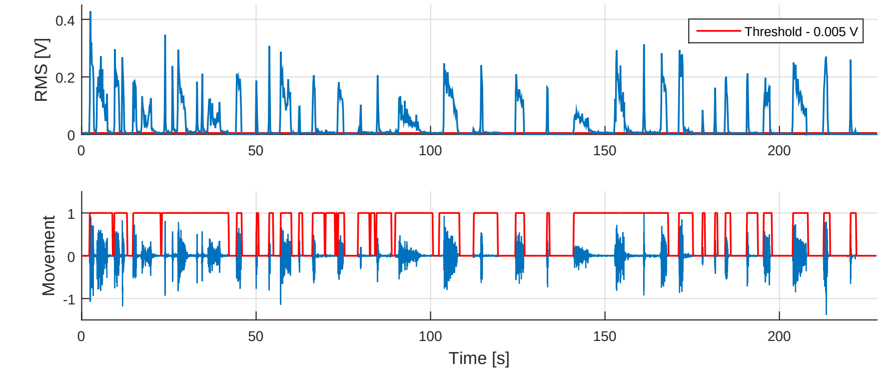
(a) Confusion matrix

Sensitivity	100 %
Specificity	100 %
Accuracy	100 %

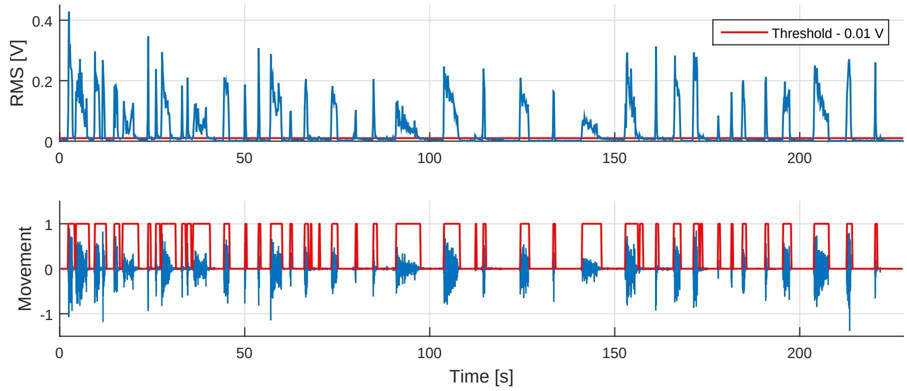
(b) S^{+}, S^{-} & accuracy

Table 5.2: Performance with $T = 0.02$ V

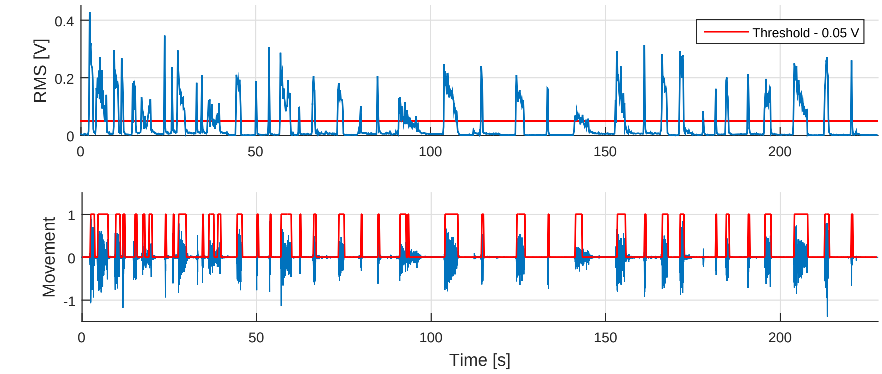
Other thresholds ($T = 0.005$ V, $T = 0.01$ V, $T = 0.05$ V and $T = 0.2$ V) are tested and the results are shown in Figure 5.4. Method performances for the different thresholds are represented in Tables 5.3, 5.4, 5.5 and 5.6. The higher the threshold, the lower sensitivity and the higher specificity. Concerning the overall accuracy, this one raises acceptable values in a specific interval. In this case, this interval is approximatively: $T = [0.015, 0.05]$ V. A lower threshold than the chosen one results in apparent muscle duration that is longer than actual whereas a higher threshold leads to a reduced duration or even until false negative classification. This issue is particularly visible in Figure 5.4d. Therefore, the choice of the threshold is a significant parameter and it depends on the noise and the gain configuration of the sEMG sensor. Nevertheless, the threshold choice should be not changed at every recording considering the acceptable threshold interval. Moreover, the threshold could be different for other muscles studied. In this recording configuration, a threshold of 0.02 V provides an excellent trade-off between classification response time, sensitivity, specificity and accuracy.



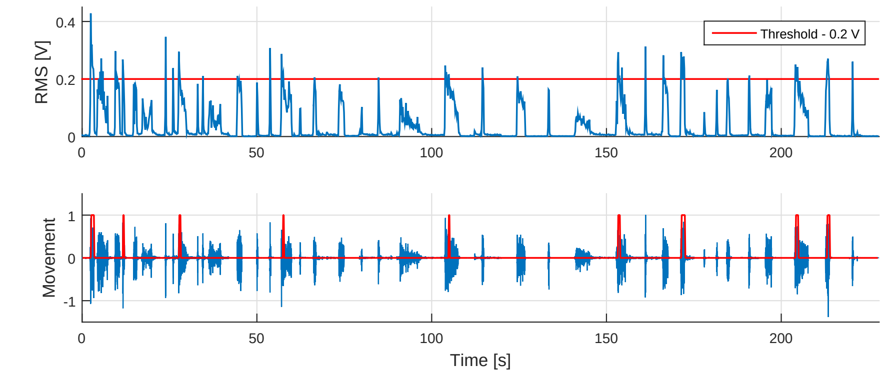
(a) $T = 0.005\text{V}$



(b) $T = 0.01\text{V}$



(c) $T = 0.05\text{V}$



(d) $T = 0.2\text{V}$

Figure 5.4: Threshold tests

Actual Class	Positive	Negative
Positive	39	0
Negative	15	25

Predicted Class (columns)

(a) Confusion matrix

Sensitivity	100 %
Specificity	62.5 %
Accuracy	81 %

(b) S^+, S^- & accuracy

Table 5.3: Performance with $T = 0.005$ V

Actual Class	Positive	Negative
Positive	38	1
Negative	5	35

(a) Confusion matrix

Sensitivity	97.4 %
Specificity	87.5 %
Accuracy	92.4 %

(b) S^+, S^- & accuracy

Table 5.4: Performance with $T = 0.01$ V

Actual Class	Positive	Negative
Positive	37	2
Negative	0	40

(a) Confusion matrix

Sensitivity	94.8 %
Specificity	100 %
Accuracy	97.5 %

(b) S^+, S^- & accuracy

Table 5.5: Performance with $T = 0.05$ V

Actual Class	Positive	Negative
Positive	9	29
Negative	0	40

(a) Confusion matrix

Sensitivity	23 %
Specificity	100 %
Accuracy	62 %

(b) S^+, S^- & accuracy

Table 5.6: Performance with $T = 0.2$ V

5.2 Intention estimation with FES

During FES application, SMUAPs synchronize to give the M-wave. Thus, the sEMG signal is not random anymore. The amplitude of the M-wave could be a parameter to notice if a movement is triggered by FES. To elicit a movement the stimulation has to be strong enough. Thus, the maximum M-wave amplitude is above a specific threshold when FES triggers a movement.

5.3 Application in stroke rehabilitation

Intention estimation without FES application on the same muscle could be useful in bilateral rehabilitation. The intention is recorded on the healthy biceps and the other arm, the disabled one, can be equipped with a motorised exoskeleton or FES can be applied on the muscle. The motor or the FES is controlled using the intention estimation of the other arm. If the patient wants to move its affected arm, he can perform a contraction using the other one. This mirror therapy has been proved to have benefits given that both arms are active. Thus, neural activity and the mobility of the disabled arm show improvements. However, intention estimation provides a binary information: movement wanted or not. Thus, no graduation is possible or just using the time of contraction of the healthy arm. This technique does not allow precise or specific movement. Secondly, the sEMG could record the biceps which is in conjunction with the exoskeleton. In this configuration, if the patient wants to move his/her affected arm whereas his/her muscles does not allow to perform the movement, the motor can allow a certain movement. Finally, FES could be applied on the muscle whose intention is estimated. In this case, if any activity of the muscle is detected, a contraction is elicited using electrical stimulation.

Chapter 6

Force estimation

In this chapter, force estimation is firstly analysed without FES application in the case of isometric contraction and some keys to study dynamic contraction are given. The estimation is performed using normalisation methods. Secondly, the estimation during FES application is briefly described. Finally, examples of application in stroke rehabilitation are provided.

The estimation of the force exerted by a muscle can provide attractive information for actuator control or FES application. Nevertheless, no quantitative relationship function has been found to describe the link between sEMG signal and force. An equation linking both will be really useful but seems complicated to find due to the randomness of the sEMG signal and its high number of influencing factors [8][25]. Some factors are related to the recording itself (extrinsic factors): configuration and placement of electrodes, for example. Physiological, anatomical features (intrinsic factors) influence the signal amplitude as well. Qualitative estimation can be made using the well-known fact that muscle activity increases with the force exerted by the muscle. Some research has demonstrated that the RMS value and TC (turn count) increase linearly according to the force [3]. Other studies have shown that the increasing of RMS value is non-linear. Actually, the linearity depends on the muscle. For example, the relationship for the first dorsal interosseus (FDI) is linear whereas for the biceps and the deltoid, it is non-linear [28]. For small muscles, such as FDI, the dynamic range of the stimulation fiber frequency is large and the most of MUs are recruited at low force level. In contrast, in large muscles, such as the biceps and deltoid, the dynamic range is small and the MU recruitments occur all along the force increase, providing less linearity [9]. Given all the influencing factors, recordings from different subjects and different sessions are meaningless and no comparable. The RMS increase provides only information of augmentation or reduction of the force exerted by the muscle during a session. Hence, a normalisation process is appropriate to allow comparison and thus overcomes the the human body heterogeneity problem.

6.1 Force estimation without FES

Generally, the normalisation is simply the division of the sEMG signal by a reference sEMG. The reference signal is a sEMG signal recorded during a specific task recorded with the same configuration of muscle and same recording equipment [29]. This reference signal must be easily repeatable for different persons who will be compared. A number of reference exists in this area. Haliki et al. summarizes them into four distinct groups [29]:

- **Maximum activation levels during maximum contractions**
  This method uses the muscle activity from a maximum isometric contraction or dynamic contraction at a specific range of joint angle.

- **Peak or mean activation levels obtained during the task under investigation**
  This reference can be used during walking [30], cycling [31] or biceps curls exercises [32] for example.

- **Peak to peak amplitude of the maximal M-wave**
  This normalisation approach is used during application of external stimulation such as FES.

- **Activation levels during submaximal isometric contractions**
  This reference can be used for patients who experience difficulty in performing a maximal contraction. Hence, a specific weight can be lifted by the patient and serve as a reference. However, with this normalisation technique, comparison between subjects can not be done. In our case, it is not a problem given that the importance is the evolution of the performance of the patient. This technique could be interesting.

The normalisation process should be done at every recording.

It is important to note that normalisation is not necessary for all signal recordings. First, when spectral analysis is performed, for example for fatigue estimation [29]. Fatigue assessment will be explained in details in the next section. Second, when the sEMG signal is decomposed into its motor unit action potential using the wavelet technique, normalisation is not necessary as well. Finally, normalisation is not necessary for the muscle time activation [29].

Isometric contraction

Isometric contraction is the easiest contraction to study: less factors influence the sEMG signal. The Maximum Voluntary Isometric Contraction (MVIC) is the most commonly used of the multiple normalisation techniques. As recommended by [5], a MVIC normalisation method consists of these following steps:

1. 6 seconds MVICs of the muscle of interest (in this case, the biceps) are recorded. Between each contraction, it is important that the muscle has time to recover. The rest time has to be at least 2 minutes [25].

2. RMS value of the sEMG signal is calculated. Here, a window of 150 samples that means 150 ms with 0% of overlap are used.

3. The middle 2 seconds of each MVIC are taken

4. The 3 segments of RMS values are averaged

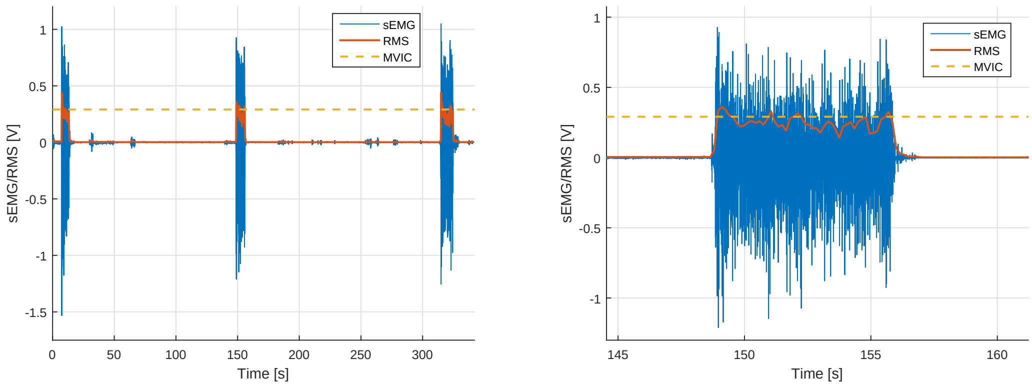
5. The maximum of the previous average is considered as the MVIC value

6. By now, the RMS value will be divided by the MVIC value providing an idea of the contraction strength according to the MVIC.

The MVIC from biceps was recorded in this research when the upper arm was at 90 degrees and the forearm was flexed at its maximum as illustrated in Figure 6.1. This study was approved by the Human Ethics Committee, University of Canterbury (HEC 2015/53/LR-PS).

Figure 6.1: Elbow configuration for the MVIC value evaluation

Steps 1 and 2 of the MVIC normalisation method are illustrated in Figure 6.2.



(a) 3 MVICs (b) Zoom

Figure 6.2: Illustration of the MVICs

The middle 2 seconds of the three MVICs and their mean are shown in Figure 6.3. The MVIC value is estimated at MVIC = 0.2908 V.

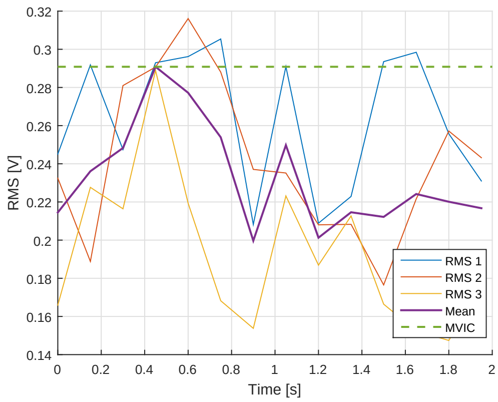
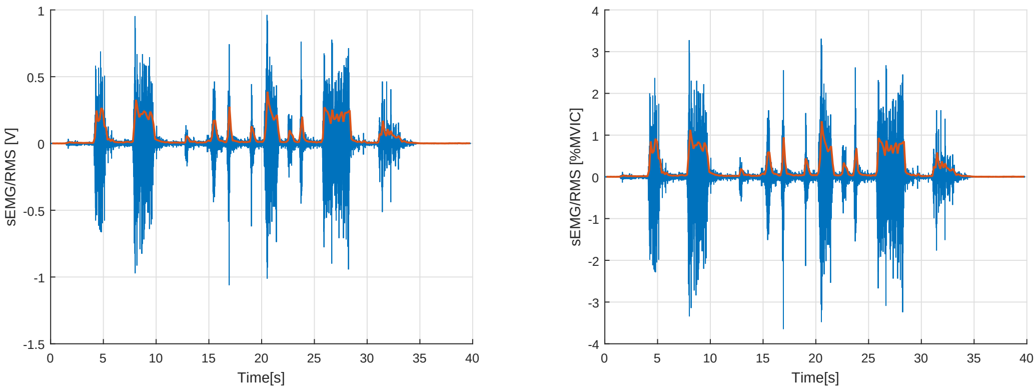


Figure 6.3: Middle 2 seconds of the three MVICs and the mean RMS value

By now, sEMG signal can be recorded and force exerted by the muscle can be estimated according to the MVIC. To do so, the RMS value is simply divided by the MVIC value. Figure 6.4 represents the impact of the normalisation in a contraction train of the biceps. This sEMG signal is recorded on the same subject shortly after the MVIC value evaluation. In Figure 6.4b, the RMS value is expressed according to the MVIC value after the normalisation. Several contractions are close to the MVIC. Moreover, the RMS value exceeds 1 twice, mainly for one contraction. This can be due to an imperfect test evaluation for the MVIC value. No report expressing a high-quality test which allows to generate the muscle maximal activation exists, to the author knowledge.



(a) Before MVIC normalization

(b) After MVIC normalization

Figure 6.4: Effect of the normalisation on the sEMG signal (blue = sEMG signal and red = RMS value)

In conclusion, MVIC normalisation before each session seems a good approach to assess the force exerted by a muscle. To evaluate the reliability and the performance of this method several recordings with different weights could be done after the normalisation process. More precisely, during the same session and with resting time between the recordings, a subject could lift successively different dumbbells with a constant position providing an isometric contraction. These data could be shown the convergence towards the MVIC value of the RMS value if the weight increases.

Dynamic contraction

Anisometric contraction provides more non-stationarities in the sEMG signal. For example, the shape of SMUAPs is modified because the relative position between fiber and electrode change during the contraction. The faster the movement, the more large non-stationarities [25]. Thus the relationship between the force and the sEMG signal amplitude is completely alterated.

Nevertheless, force can be estimated during a dynamic contraction. For this purpose, the signal has to be divided in epochs with near-isometric conditions. Force between the successive epochs is then extrapolated. For cyclic dynamic contractions such as walking or biceps curls, epochs can be extracted at specific moments of the movement. Afterwards, epochs can be compared at specific time. Thus, the impact of non-stationarities of the signal are reduced given that the comparison is performed during same conditions [25]. Concerning the normalisation, it is preferable to use as reference the maximum dynamic and ideally isokinetic contraction. In other words, the subject has to perform a maximum dynamic contraction for the entire range of motion of the joint. Then the sEMG data is normalised using the sEMG signal-angle curve.

6.2 Force estimation with FES

Another technique has to be used instead of the MVIC method during an electrically evoked contraction. This method normalizes the sEMG signal using the peak to peak amplitude $PtpA$ of the maximal M-wave [29]. Figure 6.5 shows parameters which characterize the M wave including the $PtpA$. $PosT$ is the time between the stimulus artifact and the positive peak, $PtpT$ is the peak to peak time and $Area$ is the area of the two peaks.

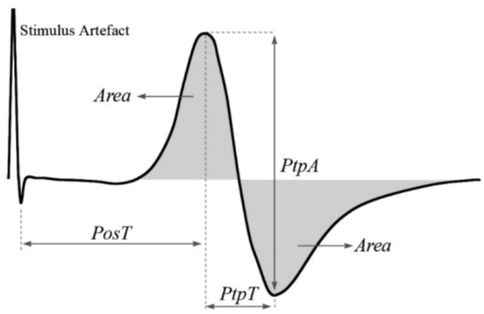


Figure 6.5: M wave and its parameters [4]

The maximal M-wave is found in increasing the amplitude of the stimulation till the $PtpA$ achieves a plateau. This $PtpA$ is then used to normalise the sEMG signal under recording of the same muscle and same investigated tasks.

6.3 Application in stroke rehabilitation

Individuals who had a stroke are able to produce maximum activation levels using the same MVIC tests as healthy individuals [29]. However, if MVIC provides pain or other disconfort, the normalisation may be done using the peak or mean activation levels obtained during the task under investigation. Some studies have been done concerning the normalisation of sEMG signal after a stroke [33] [34].

Force estimation could be useful in the rehabilitation of stroke. First, patient progression can be evaluated. MVIC of the biceps altered due to the stroke may be recorded at each session. The MVIC value should be increased as function of rehabilitation. This increase demonstrates the augmentation in muscle strength due to the rehabilitation using FES or not. Sabut et al. studied the tibialis anterior muscle from hemiplegic patients having drop foot due to stroke. Patients were trained with FES. After 12 training weeks, MVIC value increased by 83.5% [35]. Second, bilateral control can be performed using FES. The sEMG signal is recorded on the healthy arm. From this recording, the force is estimated according to MVIC. This force information can be used for the FES application on the disabled arm for example. The application will be proportional to the exerted force by the unaffected arm. The actuator which is in conjunction of the exoskeleton can be also activated in function of the force exerted. Finally, if FES may be applied on the same muscle which the sEMG signal is recorded, the amplitude of the FES may be proportional to the level of force recorded by the sEMG.

Chapter 7

Fatigue estimation

The present chapter investigates how to estimate localized muscular fatigue. First of all, fatigue is introduced and explained. Second, different methods to assess the fatigue are described. Third, an experiment is conducted to evaluate the fatigue in the biceps using spectral values (mean power frequency and median power frequency). Fourth, some clues to study dynamic and evoked electrical contractions are given. Finally, fatigue assessment is shown to be a beneficial application in stroke rehabilitation.

Fatigue assessment is important because undetected fatigue for a long period can cause injury to the subject. Physiologists typically estimate fatigue as the failure point of a muscle. This point is when the muscle contraction is not possible anymore. Psychological conditions can affect the result as well as the subject's motivation. Fatigue is evaluated after its appearance, which is a major disadvantage. Blood sample analysis is another method used often in sports medicine for evaluating fatigue. This test is based on the lactate contraction measured in the muscle. Blood samples are extracted at different times providing an estimation of the fatigue evolution during a task. However, real-time assessment is not possible with this method. Moreover, blood lactate tests provide information for the global state of fatigue rather than for a specific muscle. These two weaknesses can be overcome by the use of the sEMG signal. Indeed, sEMG signal characteristics evolve during a task producing fatigue. The fatigue estimate with sEMG signal is called localized muscular fatigue. The advantages of fatigue assessment using sEMG signal are multiple [36]: non-invasiveness, real-time evaluation, fatigue of a particular muscle, correlation with biochemical and physiological change in muscles during fatiguing.

7.1 Physiological explication

In 1912, Piper discovered [37] a slowdown in the sEMG signal during a sustained contraction. This slowing is actually a frequency shift towards the lower frequencies of the signal power spectrum. A decade later, sEMG amplitude increase during fatigue is observed by Cobb [38]. Actually, these two phenomena are related together. By now, some physiological mechanisms have been shown to explain these two observations. During localized fatigue, three modifications occur: conduction velocity modification, motor unit recruitment and motor unit synchronisation [39]. As a result, the sEMG signal changes due to fatigue.

Conduction velocity (CV) of the fibers, i.e. the propagation velocity of the action potential along the fibers, is reduced due to a decrease in intracellular pH. The latter is caused by the lactic acid accumulation induced by a blood flow reduction during the contraction [25]. The lactid acid is a metabolic by-product of the muscle contraction. The conduction velocity reduction provokes a shape change of the SMUAP and thus a power spectrum shift. As fatigue progresses, the CU slows and the greater lower frequency contents. Moreover, as tissues act as a low-pass filter, more energy is received by the surface electrodes. Hence, during fatigue tasks, the amplitude increase can be explained as a result of conduction velocity diminution.

Conduction velocity modification is not the only responsible of the amplitude increase and the frequency shift. In order to keep the constant force, motor units are recruited, providing an increase of the sEMG signal. Some SMUAP synchronizations occur during a sustained contraction inducing low frequency content and amplitude increase of the sEMG signal. Nevertheless, these two factors have less impact on the sEMG signal modification [15]. Moreover, these modifications are now put into question by several studies.

Localized fatigue can cause localized pain, tremor and the impossibility to still perform a contraction [39]. Therefore, the estimation of fatigue can potentially improve patient comfort and compliance with rehabilitation.

7.2 Estimation methods

The shift to lower frequency has demonstrated to be an appropriate approach to assess local muscle fatigue [15]. The periodogram is the mostly used [40] to evaluate the power spectral density (PSD) of the sEMG signal. Periodogram is defined as the absolute value of the Fourier transform of the signal divided by the length of the signal:

$$\mathrm{PSD} = \frac{1}{N} \mid \mathrm{fft}\,(x) \mid^2 \tag{7.1}$$

The mean power frequency MNF is simply the average frequency of the spectrum. MNF is evaluated as:

$$MNF = \frac{\int_0^{\frac{f_s}{2}} f \times P(f)df}{\int_0^{\frac{f_s}{2}} \times P(f)df} \tag{7.2}$$

where $P(f)$ is the PSD of the signal at a specific frequency f and f_s is the frequency sample.

The median power frequency MDF is the frequency value which divides the spectrum into two parts with the same area under each part. MDF is calculated using the equation below:

$$\int_0^{MDF} PSD(f)df = \frac{1}{2}\int_0^{\frac{f_s}{2}} PSD(f)df \tag{7.3}$$

Other methods have been investigated to assess localized muscular fatigue. Here are the major ones [41],[19],[8]:

- Wavelet transform
- RMS value increasing
- Autoregressive modelling

Nevertheless, MDF and MNF values are the most used in the literature to evaluate fatigue.

It is important to try to respect these assumptions during the fatigue estimation[25]:

- isometric contraction
- constant force
- contraction greater than 30% of MVIC

The isometric condition is necessary for detecting fatigue. Indeed, during anisometric contractions, a large number of factors influence the SMUAP shape. Hence, the shape modification and spectral modification cannot be only attributed to a conduction velocity reduction. The second requirement is due to the fact that temporal and spatial recruitments occur if the force increases. Thus, the sEMG amplitude increases and the frequency contents are modified. The last assumption is required because at this contraction level the blood flow becomes to be occluded. As a result, by-products, such as lactic acid, accumulate.

7.3 Experiment during isometric contraction

The localized muscular fatigue is evaluated on the biceps. The experiment is performed for an isometric contraction, that means without change in the muscle length. For that purpose, several dumbbells (4 kg, 7 kg and 11 kg) were used to provide a constant force. Concerning the elbow configuration, the arm and the forearm are at right angle as shown in Figure 7.1. This position is maintained during the entire experiment. This study was approved by the Human Ethics Committee, University of Canterbury (HEC 2015/53/LR-PS).

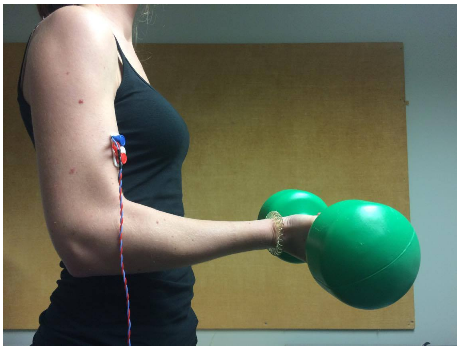


Figure 7.1: Fatigue test configuration on subject 1

Three healthy subjects participated at this experiment. Their characteristics are summarized in Table 7.1. The subjects were asked to carry the weight and to keep their elbow at 90° until muscle tremors and pain feeling occur.

	Sex	**Physical condition**	**Age**	**Stroke victim**
Subject 1	Female	Poor	22	No
Subject 2	Male	Very good	24	No
Subject 3	Male	Very good	22	No

Table 7.1: Subject detailed

The signal is recorded as before at 1000 Hz. The signal is divided into several epochs. The window length of 1 second is chosen as recommended by [19]. Every 1 s, the periodogram is evaluated and spectral parameters (MPF and MNF) are extracted. Therefore, MDF and MNF evaluated in real-time and thus fatigue may be assessed.

Figure 7.2 shows the sEMG signal and MNF and MDF values according to time for the subject 1. She carried a 4kg dumbbell during 112 s.

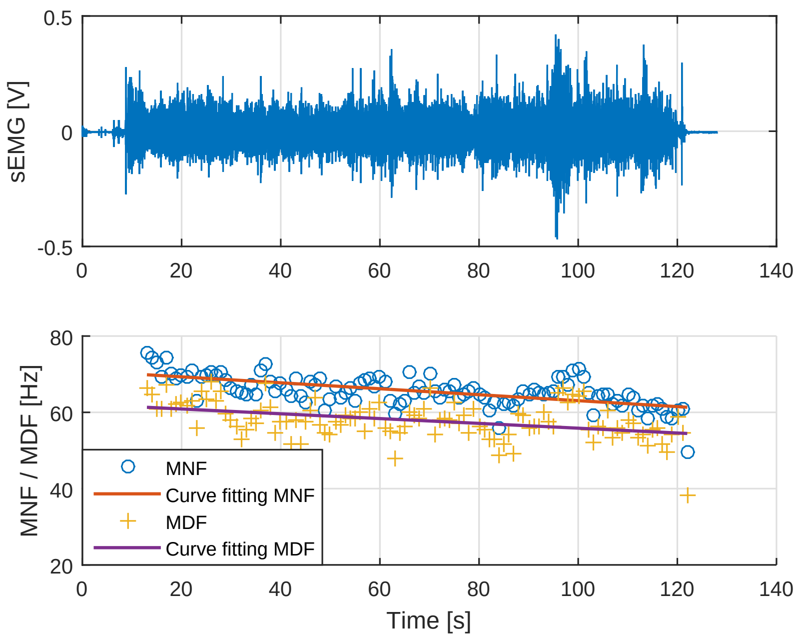


Figure 7.2: sEMG and MNF and MDF evolution during fatigue test - Subject 1 with 4 kg weight

After the end of recording, a curve fitting is applied to illustrate the decrease of the spectral parameters. This decrease is interpolated using a linear least-squares fit. The `polyfit` function provided by Matlab approximates the decrease of the MNF and MDF values as:

$$\mathrm{MDF}(t) = 60.9184 - 0.0506 \times t \tag{7.4}$$
$$\mathrm{MNF}(t) = 69.6886 - 0.0679 \times t \tag{7.5}$$

As demonstrated by the slope of these two previous equations, the decreases of the MNF and MDF values are not significant. After a rest of at least 2 minutes, the subject is asked to carry a heavier weight, i.e. 7 kg. Results are represented in Figure 7.3.

Several important information can be extracted from Figure 7.3. First, the spectral parameters decline more rapidly as shown by the gradient in the curve fitting equations:

$$\mathrm{MDF}(t) = 68.9403 - 0.5961 \times t \tag{7.6}$$
$$\mathrm{MNF}(t) = 79.0583 - 0.5968 \times t \tag{7.7}$$

where t is the time in seconds.

Second, the test duration is obviously shorter. Third, the muscle activity is greater. Indeed, sEMG amplitude is higher due to more force needed to carry the weight. Finally, initial MDF and MNF values are shifted to higher values.

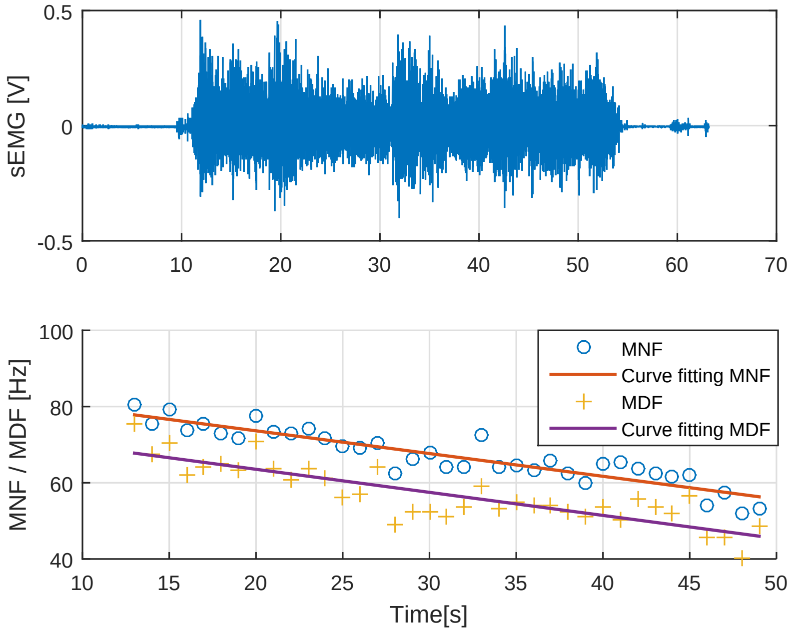
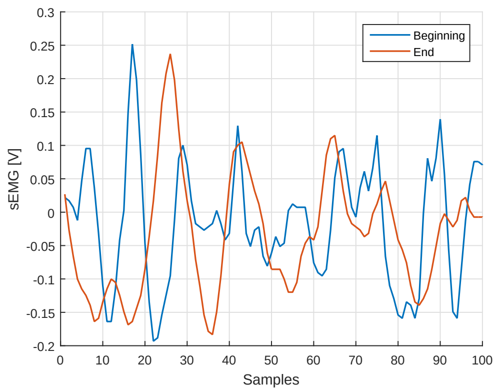
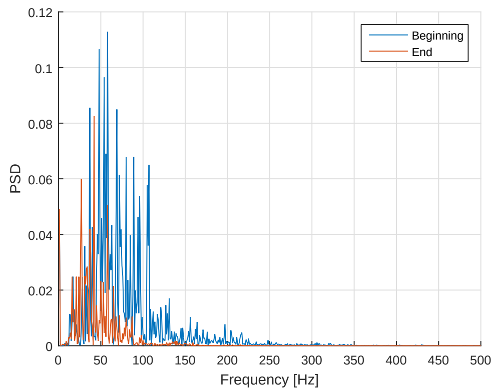


Figure 7.3: sEMG and MNF and MDF evolution during fatigue test - Subject 1 with 7 kg

Figure 7.5 illustrates the evolution of sEMG signal due to fatigue. The data comes from the recording shown in Figure 7.3. 'Slowing' of the sEMG signal is demonstrated by Figure 7.4a. Two 0.1 s periods of the sEMG signal are compared: one period at the start of the contraction and the other one at the end. Moreover, Figure ComparaisonPSD shows two periodograms evaluated at the beginning and the end. The frequency shift toward the left is visible.



(a) sEMG signal during 0.1 s



(b) Periodogram over a window of 1s

Figure 7.4: sEMG signal comparison between the beginning ($t = 15s$) and the end ($t = 45s$) of the sustained isometric contraction

As previously noted, experiments are performed on several subjects with several weights. The experiments on the same subject are performed during the same period of the day with identical sensor configuration. Resting time of at least 2 minutes is taken between recordings. All results are summarized in Table 7.2.

	MDF(t) [Hz]	**MNF(t)** [Hz]	**Duration** [s]
Subject 1 - 4 kg	$60.9184 - 0.0506 \times t$	$69.6886 - 0.0679 \times t$	112
	$59.3842 - 0.0246 \times t$	$70.5367 - 0.0235 \times t$	110
Subject 1 - 7 kg	$68.9403 - 0.5961 \times t$	$79.0583 - 0.5968 \times t$	40
	$71.8358 - 0.6663 \times t$	$79.3365 - 0.6647 \times t$	45
Subject 2 - 4 kg	$88.17220 + 0.0141 \times t$	$99.3688 + 0.0159 \times t$	492
Subject 2 - 7 kg	$90.7692 - 0.0569 \times t$	$99.7392 - 0.0692 \times t$	100
Subject 2 - 11 kg	$93.5100 - 0.2780 \times t$	$102.8878 - 0.3035 \times t$	90
Subject 3 - 7 kg	$78.3686 - 0.0148 \times t$	$98.2557 - 0.0256 \times t$	171
Subject 3 - 11 kg	$83.3526 - 0.0627 \times t$	$92.7828 - 0.0763 \times t$	90

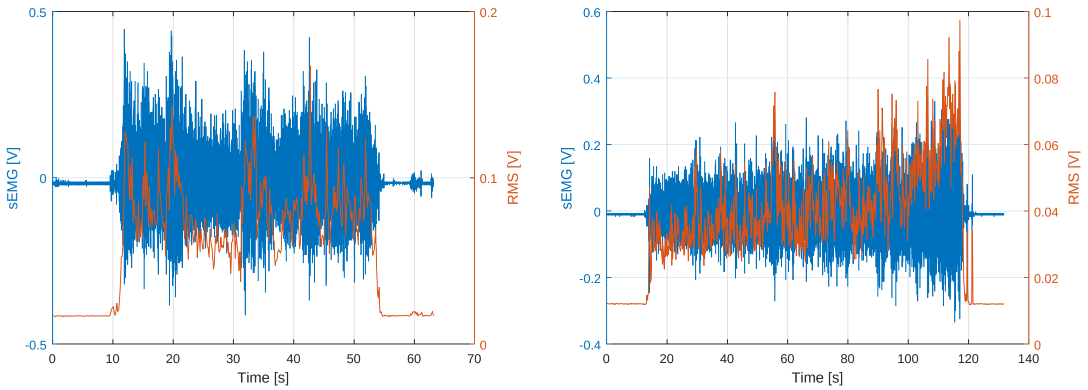
Table 7.2: Experimental fatigue results

Many observations may be extracted from this data set:

- For the same subject, the higher the effort is, the higher the MDF and MNF initial values are. This could be explained by the fact that the more muscle strength needed, the more fibers involved, the more SMUAPs overlapping, the larger high frequency contents. Therefore, the MDF and MNF initial values are a possible measure of muscle strength. Moreover, the higher weight, the stepper the gradient, the faster MDF and MNF value decline, the lower experiment duration: fatigue occurs faster.
- The slope is higher for MNF measurement than MDF. However, the difference is not significant. Both of them may be used for the fatigue assessment.
- The better the subject is trained, the higher the MDF and MNF values are. This can be explained by the amount of subcutaneous fat tissue between the biceps and the surface electrodes. The thicker the fat tissue, the more important the low-pass filtering is. As a result, MDF and MNF values are greater for trained subjects.
- If the weight is too light, the curve slope provides few or no information concerning fatigue. This observation can be due to the fact that the force exerted has to be assumed greater than 30% of MVIC. As illustration shows, for the subject 2 with a 4 kg dumbbell, MDF and MNF values have an increase tendency.

Nevertheless, comparisons between subjects are problematic. A great number of factors can influence the data, thus the conclusion. For example, the electrode positions against the biceps among subjects as close to identical as possible. However, it is almost impossible to assure this similarity. Other measurements have to be conducted to confirm these observations.

Another approach is used in several studies [3] [39]. The researchers use the increase of the RMS value during the fatigue test. However, in the most sEMG signal recording of this experiment, RMS growth is not really observed as illustrated in Figure 7.5a. However, for some recording especially for the subject 3, significant RMS value increasing according to time is found as shown in Figure 7.5b. Moreover, as said previously, time analysis requires normalization in contrast of frequency analysis. Hence spectral parameters are preferred for fatigue assessment.



(a) Subject 1 with 7 kg weight

(b) Subject 3 with 11 kg weight

Figure 7.5: RMS value evolution during fatigue test

7.4 Dynamic contraction fatigue

The final goal of the fatigue estimation is to evaluate it during a flexion/extension movement of the arm. Thus, the contraction is not anymore an isometric contraction but a dynamic contraction. Therefore, several modifications have to be taken into account.

Experimental conditions and fatigue assessing methods to limit non-stationarity are the following: [15]:

1. The dynamic contraction must be cyclic and the most as possible identical for every cycle. Thus, the upper arm could be fixed to the flank. Only the forearm can move, this increase the repeatability of the cyclic contraction.
2. The analysis of the MDF and MNF values is focused at a specific angle in order to attenuate the impact of non-stationarity due to the movement. For example, an angle of 45 degres during the flexion could be chosen.
3. The MDF and the MNF values are then averaged for several cycles.

7.5 Fatigue during FES

Fatigue occurs more rapidly when contraction is electrically induced [26]. Hence, fatigue evaluation during evoked contraction is important. Fatigue may be evaluated in M-wave using spectral parameters as well. Indeed, the M-wave widens as time increased. In other words, a shift to the lower frequency occurs exactly as muscle are voluntary contracted. However, M-wave RMS amplitude decreases due to the M-wave broadened which is contrary to the voluntary contraction case [26].

As explained before, during voluntary contraction, the sEMG is subdivided in several epochs of constant time (1 s). Then, the PSD is evaluated for each epoch in order to estimate MDF or MNF time evolution. In the case of electrically elicited contraction, the similar method is applied except the definition of epochs. Indeed, the signal is divided into epochs comprising N responses (M-waves) elicited by N electrical stimulus. Then, these N M-waves are averaged and this mean is used to estimate the PSD [19].

7.6 Application in stroke rehabilitation

First, improvement evaluation may be done using the MDF and the MNF values. Indeed, as demonstrated in the previous section, the stronger the muscle is, the higher MDF and MNF initial values are. As an illustration, tibialis anterior muscle from hemiplegic patients having drop foot due to stroke are trained with FES. After 12 weeks, MDF increased by 15.8% [35]. The signal recorded is a MVIC. Moreover, the slope may be used as well for progress assessment. The better the muscle is trained, the slower fatigue is. Second, fatigue may be evaluated in real-time during FES and provides to the physiotherapist information to optimize the session time. This is particularly important because the stroke patient has difficulty to feel his muscle fatigue condition [26].

Chapter 8

Elbow angle estimation

This chapter focuses on the elbow angle estimation. First, the elbow motion is explained and simplified in order to facilitate its estimation. Second, features for providing interesting information from the sEMG signal are cited. Third, an experiment is performed on an isokinetic contraction. Fourth, one method is tested to evaluate the elbow angle: adaptive neuro-fuzzy interference system. Finally, some applications in stroke rehabilitation are given. It is important to say that this chapter is more a trial. Some useful information is extracted and underlined in order to find other approaches to estimate the elbow angle.

As the sEMG signal occurs slightly before the intended movement, information may be extracted from the signal reflecting the movement before its apparition. Thus, the actuator or FES can be control to help the patient to achieve a specific movement. Hence, another interesting estimation is the elbow angle assessment.

8.1 Elbow representation, muscles involved and experimental setup

The elbow joint allows pronation/supination and flexion/extension of the forearm. Thus, the elbow consists actually of a combination of two types of joints: pivot joint and hinge joint. The pivot joint called radioulnar joint allows the rotation of the radius around the ulna. The forearm is said pronated when the palm is downward and supinated when this one is upward. The flexion and extension involve the humeroradial joint that means the hinge joint. The range of motion is 0-145 degrees (ROM). It is important to notice that to perform these two reverse movements two muscle groups (flexor and extensor) are necessary. Figure 8.1 shows the major flexor muscles whereas Figure 8.2 presents the main extensor muscles.

The main flexor muscle is the brachialis and the following is the biceps. Given that the brachialis is located below the biceps, the measurement of its electrical activity using sEMG signal is difficult. Therefore, the biceps activity is studied instead. The brachioradialis is involved in the flexion as well mainly when the forearm is pronated [5]. Therefore, the supination/pronation degree influences the biceps activity during a flexion. The triceps is the principal extensor muscle. Their activity during a flexion/extension movement is shown in Figure 8.3.

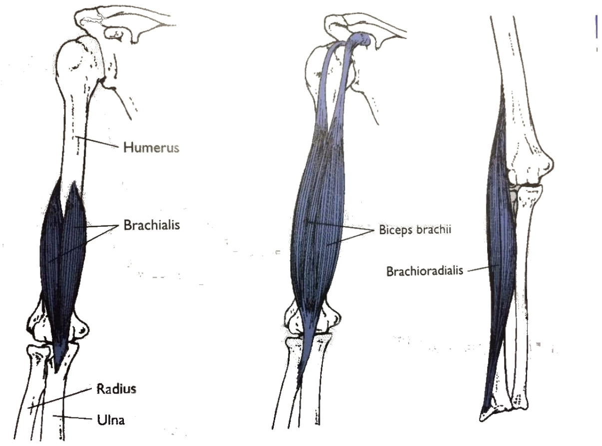


Figure 8.1: Major flexor muscles of the elbow : Brachialis, biceps and brachioradialis [7]

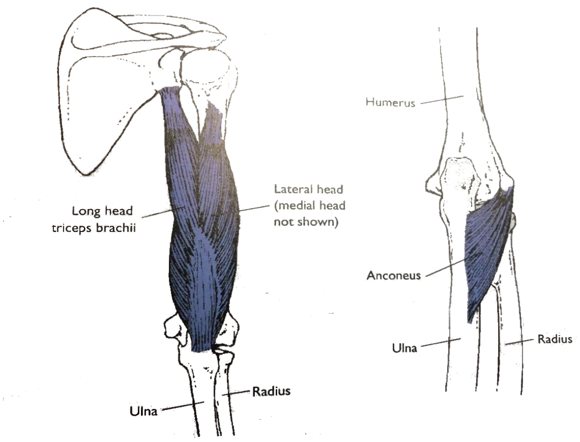


Figure 8.2: Major extensor muscles of the elbow : Triceps brachii and anconeus [7]

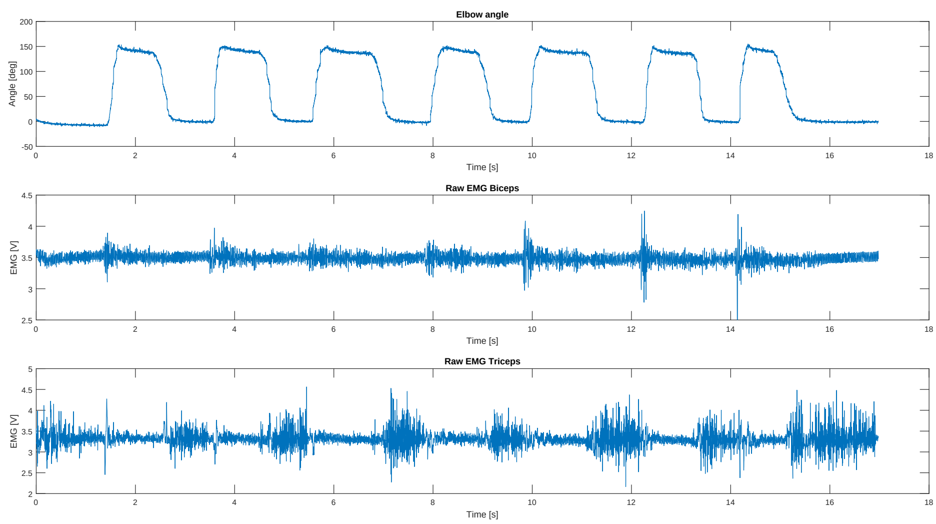


Figure 8.3: Biceps and triceps activities during a flexion/extension movement

In order to evaluate the elbow angle using sEMG signal from the biceps, several assumptions are required. First, the shoulder is fixed. The subject's arm is in vertical position close to the flank. Second, the forearm is on neutral position. Supination and pronation are not permitted. Indeed, when the forearm is supinated the biceps contributes more to the flexion given that this muscle is slightly stretched. Therefore, elbow movement is simplified as one degree of freedom (dof) movement. This dof is the elbow angle θ. Figure 8.4 represents a simple 1 dof (elbow angle θ) model of the shoulder (S), elbow (E) and hand (H). Finally, the elbow movement has to be as much as possible an isokinetic contraction. In other words, the movement speed has to be approximatively constant.

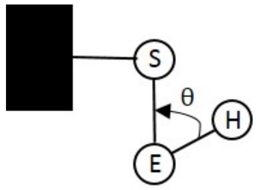


Figure 8.4: Elbow representation

8.2 Interesting features

Literature provide a great number of features [42][43][24]. A distinction among them can be done between time and frequency features. The sEMG signal x is segmented into windows of length N. The segmentation may be done with overlapping or not. The major features to extract information in the sEMG signal are the following:

Time features

- Mean Absolute Value - MAV

$$\frac{1}{N}\sum_{i=1}^{N} \mid x_i \mid \tag{8.1}$$

- Mean Value - M

$$\frac{1}{N}\sum_{i=1}^{N} x_i \tag{8.2}$$

- Zero Crossings - ZC

$$\sum_{i=1}^{N} \operatorname{sgn}(-x_i \times x_{i+1}) \tag{8.3}$$

$$\operatorname{sgn} = \begin{cases} 1 \text{ if } x > 0 \\ 0 \text{ otherwise} \end{cases} \tag{8.4}$$

- Root Mean Square - RMS

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{8.5}$$

- Waveform Length - WL

$$\sum_{i=1}^{N} \mid x_i - x_{i-1} \mid \tag{8.6}$$

Frequency features

- Autoregressive Model - AR

$$x_k = \sum_{i=1}^{p} a_i x_{k-1} + e_k \tag{8.7}$$

p is the order of the model and 4 is proved adequate for the modeling of the sEMG signal and a_i's represent the AR coefficient. As previously explained, a modification of the muscle contraction induces a spectrum change. This can be reflected by the AR coefficients. e_k represents the residual white noise.

The coefficient a_i's are found using these two recursive equations:

$$\boldsymbol{a}_i = \boldsymbol{a}_{i-1} + \boldsymbol{P}_i \boldsymbol{X}_i \left(x_i - \boldsymbol{X}_i^T \boldsymbol{a}_{i-1} \right) \tag{8.8}$$

$$\boldsymbol{P}_i = \boldsymbol{P}_{i-1} - \frac{\boldsymbol{P}_{i-1} \boldsymbol{X}_i \boldsymbol{X}_i^T \boldsymbol{P}_{i-1}}{1 + \boldsymbol{X}_i^T \boldsymbol{P}_{i-1} \boldsymbol{X}_i} \tag{8.9}$$

where $\boldsymbol{X}_i = (x_{i-1}, x_{i-2}, \cdots, x_{i-p})$, $\boldsymbol{a}_i$ vector represents the actual estimates of the AR coefficients whereas $\boldsymbol{a}_{i-1}$ resumes the previous estimates, and $\boldsymbol{P}$ is a $p \times p$ matrix. AR coefficents are evaluated within each time window. Therefore, these recursive equations are evaluated for every window and the last estimate is considered as the representative AR coefficients.

8.3 Experiment on isokinetic contraction

The sEMG signal from a biceps was recorded during extension and flexion of the elbow and was illustrated in Figure 8.5. Angle elbow was assessed in the same arm using the exoskeleton equipped with a potentiometer. The subject (subject 2) tried to keep a constant movement speed to facilitate the analysis. Therefore, contraction is supposed isokinetic. The elbow angle is normalised in order to correspond to the ROM meaning 0-145 degrees. This experiment was approved by the Human Ethics Committee, University of Canterbury (HEC 2015/53/LR-PS) as all recordings in this chapter.

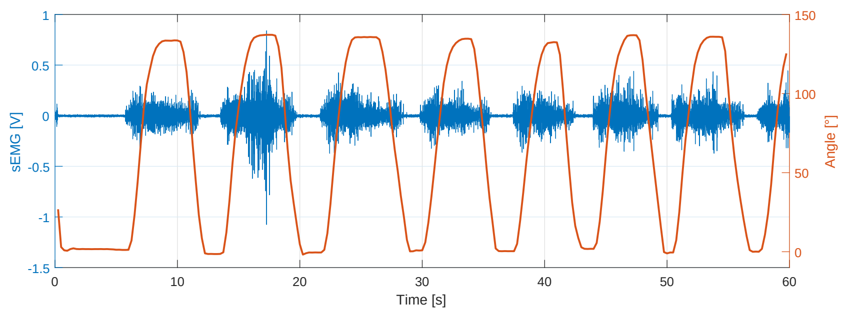


Figure 8.5: Biceps sEMG signal during isokinetic extension/flexion according to the elbow angle

Figure 8.6 illustrates the configuration during the experiment. As noticed on this figure, the exoskeleton is cumbersome. Moreover, it is difficult to stabilize it. The velcro tape has to be tightened to provide more stability. However, the tighter the tap is, the more difficult the whole ROM is to achieve and the more painful it is for the subject. Hence, another sensor to estimate the angle is desirable.

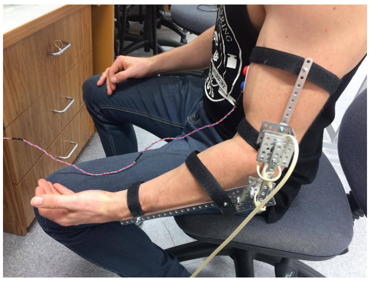


Figure 8.6: sEMG from the biceps and elbow angle during flexion/extension movements

8.3.1 Features extraction

Several features are extracted from the sEMG signal: MAV, M, WL, RMS, ZC and AR coefficients. A time window of 250 milliseconds or 250 samples given that the sample frequency is 1000 Hz as suggested by [44]. The segmentation into these windows is done with 0 % of overlap. Indeed, in the future, the angle estimation has to be performed in real time, overlapping costs more in computational time. The set of features is illustrated by Figure 8.7.

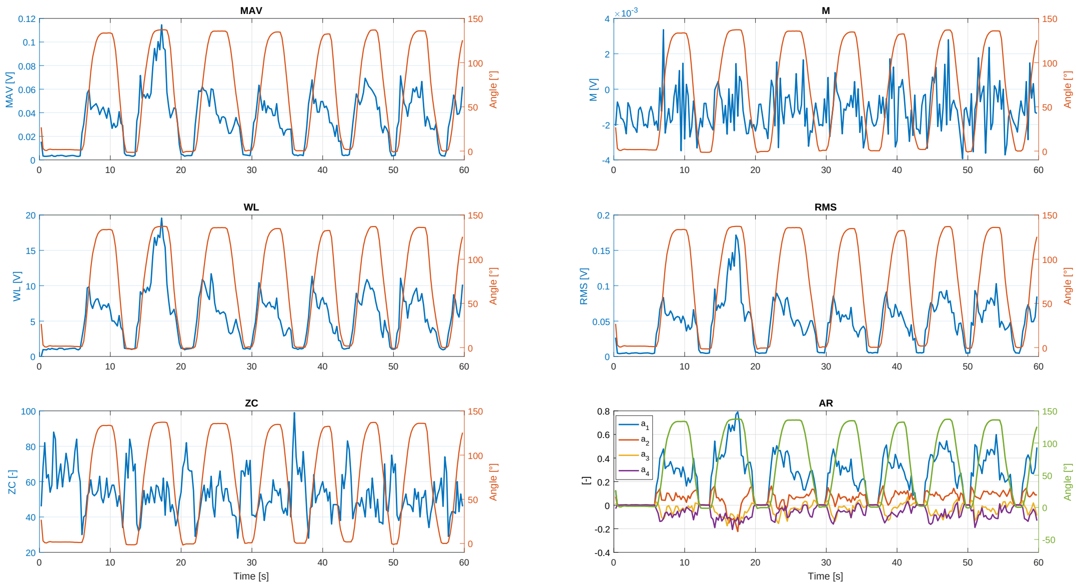


Figure 8.7: Features - MAV, M, WL, RMS, ZC and AR coefficients - during isokinetic contrations

First, Figure 8.7 demonstrates that M feature is not adequate for the angle estimation compared to the other ones. MAV, RMS, WL and a_1 features have the same behaviour. They follow the elbow angle. Moreover, it is important to notice that they seem to follow linearly the elbow angle during the flexion and not during extension. This phenomenon may be explained due that the biceps is more involved during the flexion and the triceps during the extension as demonstrated by Figure 8.3. Second, ZC feature has a different behavior. This feature reaches its maximum when the muscle is inactivated. When the muscle is not activated, the sEMG sensor records noise. Thus, the signal crosses more the reference line meaning 0 V. However, when the muscle becomes active, ZC feature has its minimal value. Then, ZC feature increases as the muscle activity develops due to the increase of high frequency contents. Finally, electromechanical delay is illustrated on Figure 8.8. The SMUAPs are triggered few milliseconds before the movement is performed. Cavanagh et al. [45] have demonstrated that the mean electromechanical delay for the biceps is 49.5 ms for eccentric contraction, 53.9 ms for an isometric contraction and 55.5 ms for a concentric contraction.

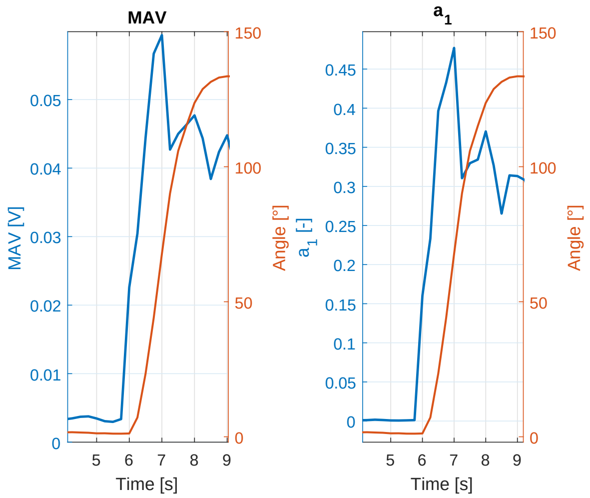


Figure 8.8: Electromecanical delay illustration with MAV and a_1 features

In order to compare different data and see if there are some differences between the recordings, another sEMG signal from the biceps is recorded on the same subject but at a different moment of the day. The sEMG signal is shown in Figure 8.9 and the set of features is displayed in Figure 8.10.

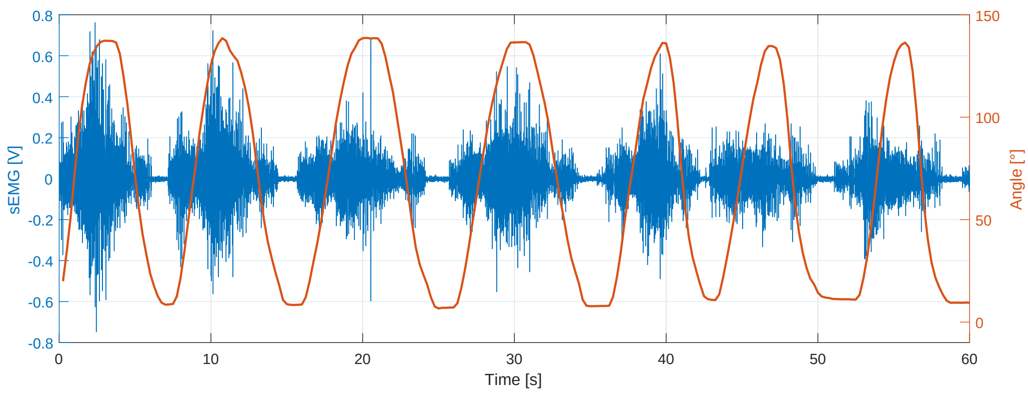


Figure 8.9: Biceps sEMG signal during isokinetic extension/flexion elbow according to the elbow angle

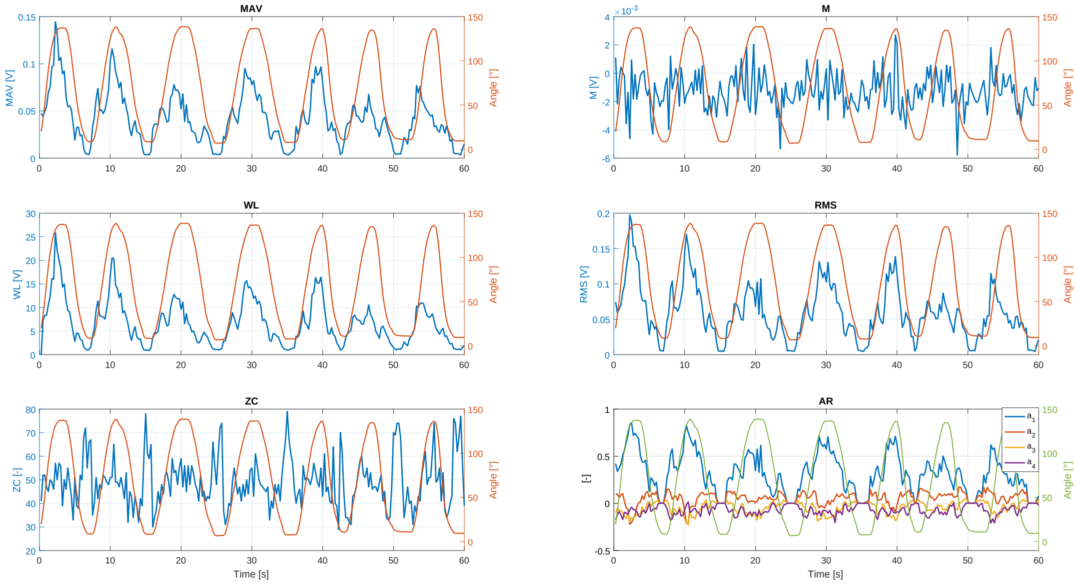


Figure 8.10: Features - MAV, M, WL, RMS, ZC and AR coefficients - during isokinetic contractions

The set of features from the second recording (Figure 8.7) shows some dissimilarities from the first one (Figure 8.10). The second recording shows a feature increase with less linearity during the flexion. Moreover, it is important to notice for this subject that the biceps is a lot involved during the extension, in contrast to other persons (Figure 8.3). This subject goes to the gym everyday and he is used to perform some exercises to increase the strength of his biceps. This higher physical condition could explain this difference.

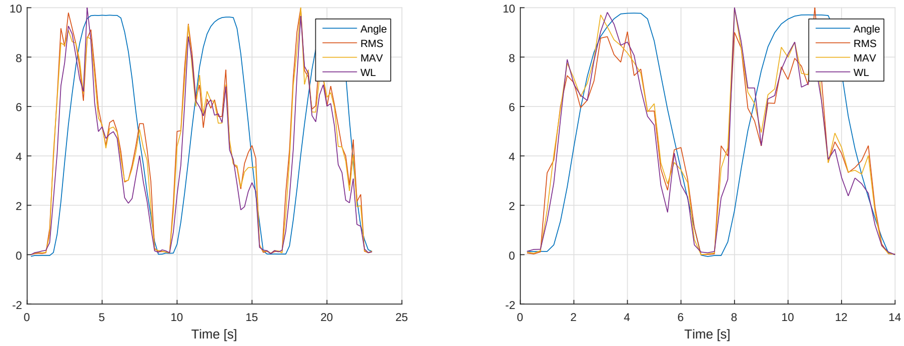
8.3.2 Adaptive neuro-fuzzy inference system

Adaptive neuro-fuzzy inference systems (ANFIS) is an artificial neural network that has the advantages of the neural network and the fuzzy logic. From an input/output data set, ANFIS creates a fuzzy interference system with membership function characteristics that maximise the map between the input and output data. ANFIS uses a back propagation algorithm to learn from the data [46].

The cyclic dynamic contraction of Figure 8.5 is used for the assessment. The set of movement is separated into two data classes: training set and testing set. The third, fourth and fifth cycles are defined as the training set whereas the testing set corresponds to the last two cycles. Three features are extracted from the two sets. Then, these features and the angle are normalised between 0 and 10. The normalisation is necessary to remove some factors like the dependence of the conditions of the electrode placement or the patient's physical condition. The normalisation is performed according to this equation, where X corresponds to a feature or the angle:

$$X_N = \frac{X - min(X)}{max(X) - min(X)} \times 10 \tag{8.10}$$

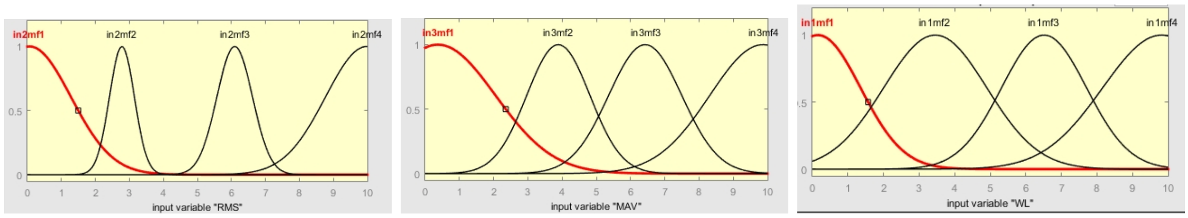
The elbow angle and the RMS, MAV and WL features are illustrated in Figure 8.11.



(a) Training data (b) Testing data

Figure 8.11: Set of features for the training and testing data

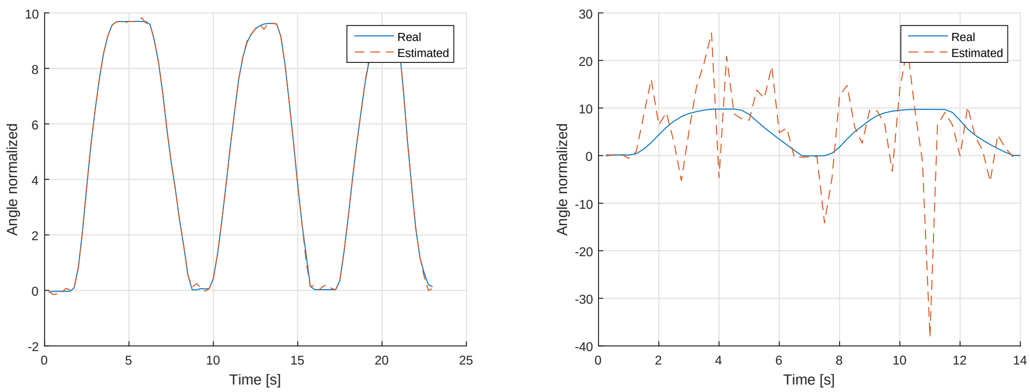
Matlab provides a `Neuro-Fuzzy Designer` toolbox. The `Neuro-Fuzzy Designer` app allows to design, train and test an ANFIS. For this purpose, the training data are downloaded in the app and different ANFIS configuration may be tested. After several trials, the Gaussian curve membership function (`gaussmf`) for the whole system is chosen because of its small error estimation in contrast to the others. Four memberships are attributed to the inputs as shown by Figure 8.12.



(a) RMS (b) MAV (c) WL

Figure 8.12: Input membership functions

Matlab performs the training in order to find links between the inputs (RMS, MAV, WL features) and the output. 64 if-then rules are created to link the inputs to the output. The estimation for the training and testing data are shown in Figure 8.13a and Figure 8.13b.



(a) Training data (b) Testing data

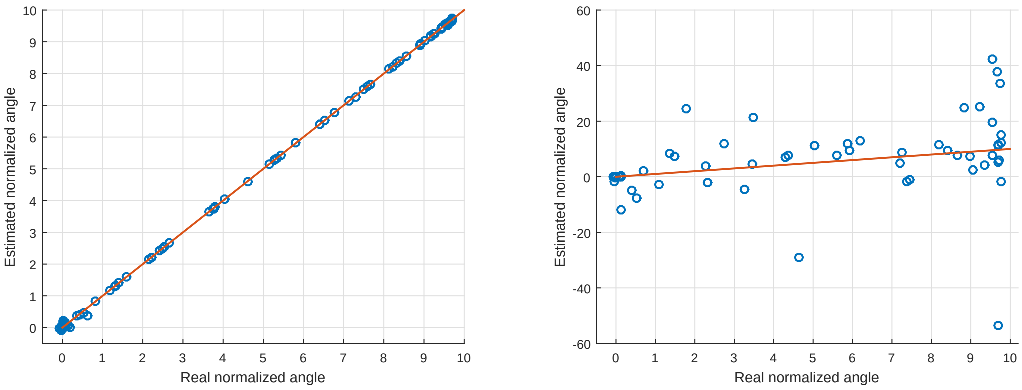
Figure 8.13: Angle estimation

Regression curves are drawn for both data sets as illustrated by Figure 8.14. R squared values for the both classes are evaluated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{8.11}$$

where y_i represents the real angle and $\hat{y}_i$ is the estimation one.

R squared equals to 0.9998 for the training set and -11.4876 for the testing set.



(a) Training data - $R^2 = 0.9998$

(b) Testing data - $R^2 = -11.4876$

Figure 8.14: Regression curves

8.4 Discussion

Good results for the training set are obtained. However, the result for the testing data is completely false. Using the training data, the estimated angle is correctly estimated because the algorithm is based on these data. To improve the estimation, some ideas can be cited. First, more training data are suitable. As shown in Figure 8.7 and 8.10, feature amplitude is different for the different cycles of the same recording. Moreover, the features have the same behaviour and thus provide practically identical information for the estimation. It could be interesting to record the sEMG signal from the triceps given that this muscle is antagonist to the biceps. Hence, their activity should be different during the flexion/extension movement and should provide complementary information. Another problem is that a specific angle can be reached during the flexion or the extension movement. The muscle activity is not the same for this two different movements. Thus, two kinds of activity represent a particular angle. Features from the biceps could have more weight for the angle estimation during flexion and features from the triceps during extension. Or another method is to distinct angles achieved during flexion from extension. In addition, the angle was not recorded by a precise sensor, this can change the map between the features and the angle for every cycle. Finally, the isokinetic condition is not well respected. To overcome this, the wanted angle to respect the isokinetic condition could be displayed on a screen as well as the actual angle. Thus, the user would know if his/her movement is too fast or to slow.

Therefore, recommendations for further analysis are:

1. Record the sEMG signal from the triceps
2. Record the elbow angle with an accurate and easy-to-use angle sensor
3. Have more data for the training set
4. Work in real-time
5. Display the angle wanted on a screen to respect the isokinetic condition

8.5 Application in stroke rehabilitation

The sEMG signal may be recorded in the damaged biceps. Given the electromechanical delay, the angle may be evaluated before the movement. Thus, the exoskeleton actuator or FES amplitude may be controlled to assist the movement.

Chapter 9

Conclusions and perspectives

All along this report, the sEMG sensor prototype has provided satisfactory results despite its low price. This sensor can be used to assess electrical muscular activity. Moreover, the sEMG signal has been shown to provide useful information for the stroke rehabilitation. First, intention estimation can be easily extracted from all kinds of contractions. Second, force estimation for isometric contraction is achievable using MVIC normalisation. However, MVIC evaluation is necessary at every session. For anisometeric contraction, it is more difficult to extract coherent information due to the non-stationary increase. Despite of these additional non-stationarities, force assessment could be performed during a cyclic dynamic contraction if the evaluation is done at specific constant time. Third, localized muscular fatigue is well identifiable during sustained isometric contraction. Concerning dynamic contraction, issues and solutions are the same than force estimation. Finally, elbow angle estimation has shown some issues and has to be further investigated.

During all the recordings, the sEMG signal depended on a lot of factors. During contraction in non isometric condition, signal non-stationarities are particularly significant. Hence, dynamic contraction is difficult to analyse. To reduce the impact of non-stationarities, cyclic dynamic contraction has to be preferred to non-cyclic dynamic contraction. Analysis should be performed for every cycle at a specific angle. Hence, an accurate elbow angle measurement should be investigated. For example, the use of several detectable markers by a camera could be positioned on the arm.

FES application has been briefly studied. A large artifact was unfortunately present as expected. To attenuate the artifact effect, further investigations are needed exploring software or hardware filtering in order to allow M-wave recording.

All sEMG signals were recorded on healthy subjects. It could be interesting to conduct these estimation methods on sEMG signals coming from a patient who had a stroke. This will allow to check, on a stroke patient, the signal amplitude versus the noise level and to validate the studied estimation methods.

Consulted physiologists mentioned that muscle atrophy estimation could be useful to improve their rehabilitation approach. Muscular atrophy is a muscle reduction due to physiological or pathological phenomena. After a stroke, muscle atrophy develops due to the patient immobility. Atrophy could be assessed using the muscular fiber diameter. The fiber diameter is proportional to its conduction velocity [25]. The larger diameter, the greater average conduction velocity, the more high frequency contents, the larger MDF and MNF values. This relation could be further explored. The muscle atrophy state could optimize the rehabilitation and provide subject progress assessment.

Another biosignal could be used instead of, or in conjunction with, the sEMG signal to reflect the muscle activity: the mechanomyography (MMG) signal. This signal records the muscle surface oscillation during a contraction. The recording may be done using contact microphone or accelerometer directly in contact with the skin. MMG signal has advantages over sEMG signal: it is not dependent of skin impedance as sweating and does not require a precise placement sensor [47].

The rehabilitation in general, not only for stroke patient, has a promising future thanks to the overall technological progress. Virtual reality is an example among others and could be interesting as mentioned by the physiologists that we met. Some recent studies have already been conducted for stroke patients and provided promising results [48].

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