Warsaw University of Technology

Objective models of EMG signals for cyclic processes, obtained from human gait

Grado en Ingeniería
en Tecnologías de Telecomunicación

Bachelor Thesis

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Abstract

The aim of this thesis is to obtain an objective model of EMG signals by signal averaging methods. As a result, a database of EMG signals corresponding to activity of 8 muscles located in legs during human gait while holding a 2 Kg load with the hands is obtained. This database will be used by the Warsaw University of Warsaw in a biomedical research.

As well, this thesis pretends to be a guide for those who want to work with EMG signals and they need to obtain a reliable model of these signals. This thesis provides a good method to obtain these models if you have already EMG signals from a cyclic process.

Contents

Introduction

Electromyography is a very useful technique in biomedicine. EMG signals are small potentials appearing at the surface of human skin during muscle work. This activity can be measured by sensors and then record the EMG signals. With a lot of records it is possible to understand how work the different muscles in different activities.

The ultimate goal of this thesis is to help researchers providing useful EMG signals data. The use of EMG is not limited to medicine. It can be used in many fields. For example, it is a good way to improve a sportive training, or maybe to improve an ergonomics design.

Another interesting use of EMG technique and very actual right now is to create a communication interface between a user and a machine. The aim is to be able to substitute the keyboard and the mouse by this system in which you control the computer contracting and relaxing muscles. This system is especially designed for people with some kind of handicap.

My own goal within this project is to take part in this research of EMG. I personally think it is a very interesting subject and I would like to contribute providing a database and a guide.

Chapter 1

EMG signals

The signals obtained when using EMG technique will be called EMG signals. The goal of the thesis is to create models with these signals so let's try to learn more about them before the methodology for obtaining models is explained.

1.1 Definition

To start learning more about EMG signals let's provide a technical definition about EMG:

"Electromyography (EMG) is an experimental technique concerned with the development, recording and analysis of myoelectric signals. Myoelectric signals are formed by physiological variations in the state of muscle fiber membranes."

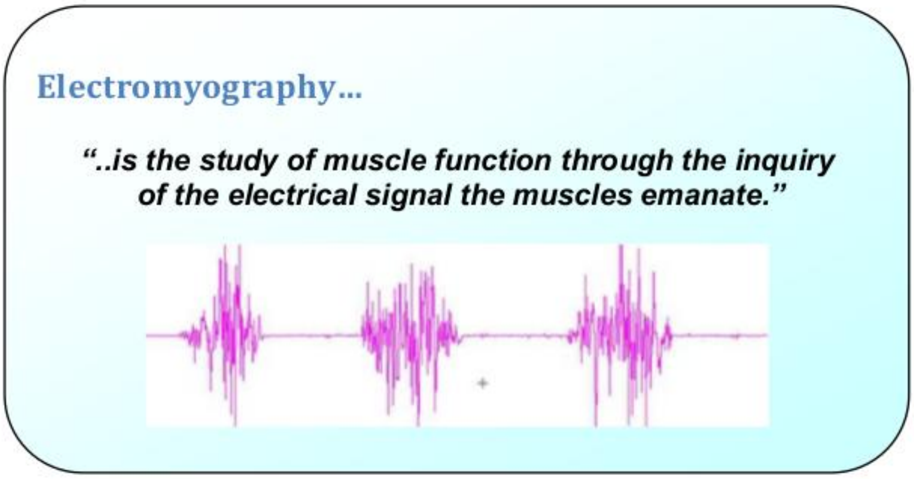


Figure 1.1: Electromyography definition

Unlike the classical Neurological EMG, where an artificial muscle response due to external electrical stimulation is analyzed in static conditions, the focus of Kinesiological EMG can be described as the study of the voluntary neuromuscular activation of muscles within postural tasks, functional movements, work conditions and treatment/training regimes.

Where do the EMG signals come from? Which is the origin of this particular kind of signals? EMG signals are small potentials appearing at the surface of human skin during muscle work. They arise due to changes in the physiological state of cell membranes in the muscle fibers. They are characterized by a relatively low frequency range (500 Hz) and a low amplitude signal (of the order of μV), making it difficult to record.

When an end-plate potential is generated at a nerve-muscle synapse, it results in a muscle fiber action potential that propagates from the synapse to the ends of the muscle fiber. The changes in the electrical potential of the muscle membrane produced by the propagation of the action potential can be measured with electrodes: such a recording is known as an electromyogram (EMG).

1.2 EMG uses

For what and for whom is useful EMG technique? EMG is used by scientists to study the neuromuscular system, by doctors for diagnosis of neuromuscular diseases and by physiotherapists to monitor the activation of muscles of a patient.

Let's see some of the typical benefits of using EMG technique. They are all related with the question "What are the muscles doing?", so the most important benefits are the following:

- EMG allows to directly "look" into the muscle
- It allows measurement of muscular performance
- Helps in decision making both before/after surgery
- Documents treatment and training regimes
- Helps patients to "find" and train their muscles
- Allows analysis to improve sports activities
- Detects muscle response in ergonomic studies

However, the uses of EMG technique are almost unlimited. For example, some scientists are developing right now a communication interface between a user and a machine to substitute keyboard and mouse by contracting and relaxing certain muscles. There is a lot of work too related with controlling different mechanic gadgets with EMG signals, like for example a robotic arm.

EMG technique is a very actual subject in scientific research. It would not be strange to see these years a lot of new products related with the EMG signals.

1.3 Acquisition

There are two main modes to acquire the EMG signals. In both of them the acquisition is developed by using electrodes. The first mode consists in inserting the electrodes inside the muscles (intramuscular electrodes). In the second mode the electrodes are placed on the surface of the skin (surface electrodes).

The study purpose determines whether surface or intramuscular electrodes are used. Surface electrodes are frequently used to assess superficial muscle activity. Intramuscular electrodes are used to derive information about the activity from muscles located deep in the body and to record motor unit activity.

For the case of this thesis, the EMG records studied were obtained using surface electrodes. The muscles analyzed are located in the legs and the aim is to see their superficial activity of these muscles during human gait.

It is enough with this information about acquisition. The topic of this thesis deals with EMG signals process, not about acquisition. How are the records obtained is not important for our purpose.

Chapter 2

Background

2.1 Context

It is time to talk about how was the situation at the beginning of the development of this thesis. It is time to locate the start point of this project.

Firstly, we must say that this thesis takes part in a bigger project, developed by the 'Warsaw University of Technology' in which many students and professors participate. The reason is that there are many data to process, so each student works just with a part of the total information collected.

The data have to be processed by humans because sometimes it is necessary to remove some samples due to problems with probes, human errors, relevant interferences...

The investigations were performed using the VICON system (motion capture system) at the University of Physical Education in Warsaw. Studies were carried out on one person in one day. The object of research was a healthy woman and she moved repeatedly after a fixed track. She had placed on her body 35 reflective markers to record the gait kinematics and 8 electrodes to record EMG signals. EMG signals and the position of reflective markers placed on the human skin were recorded at the same time (synchronously), and the location of the reflective markers and EMG sensors is not changed during the measurement.

During the experiment the object of research was holding always a load. Firstly the load was held with the left hand, later with the right hand and finally with a load in both hands. The loads had a weight of 2,4,6,8 and 10 Kg. The data analyzed in this thesis correspond with the 2 Kg load measures.

As the result of the research more than 1000 EMG waveforms synchronized with the phases of gait were obtained. Each of these signals corresponds to a single gait cycle. Finally we arrive to the start point of this thesis. From the signals obtained by this experiment now it is time to process all this data and obtain some useful information about EMG signals.

2.2 EMG sensors

As we told previously 8 electrodes were used to record the EMG signals. The purpose of these sensors is to register the activity of the different muscles studied. It is interesting to analyze how the different muscles act during human gait. The sensors are distributed by different muscles all over the legs. The specific location of the different electrodes is shown in the Figure 2.1 and the Figure 2.2. The name used in this thesis and the concrete name of the muscle can be shown in Table 2.1 and Table 2.2.

Most of the important limb and trunk muscles can be measured by surface electrodes (marked in yellow in Figure 2.1 and Figure 2.2). However, for this thesis only the muscles marked with a big colored circle are studied. The names of these muscles appear in the Table 2.1 and Table 2.2.

Frontal View

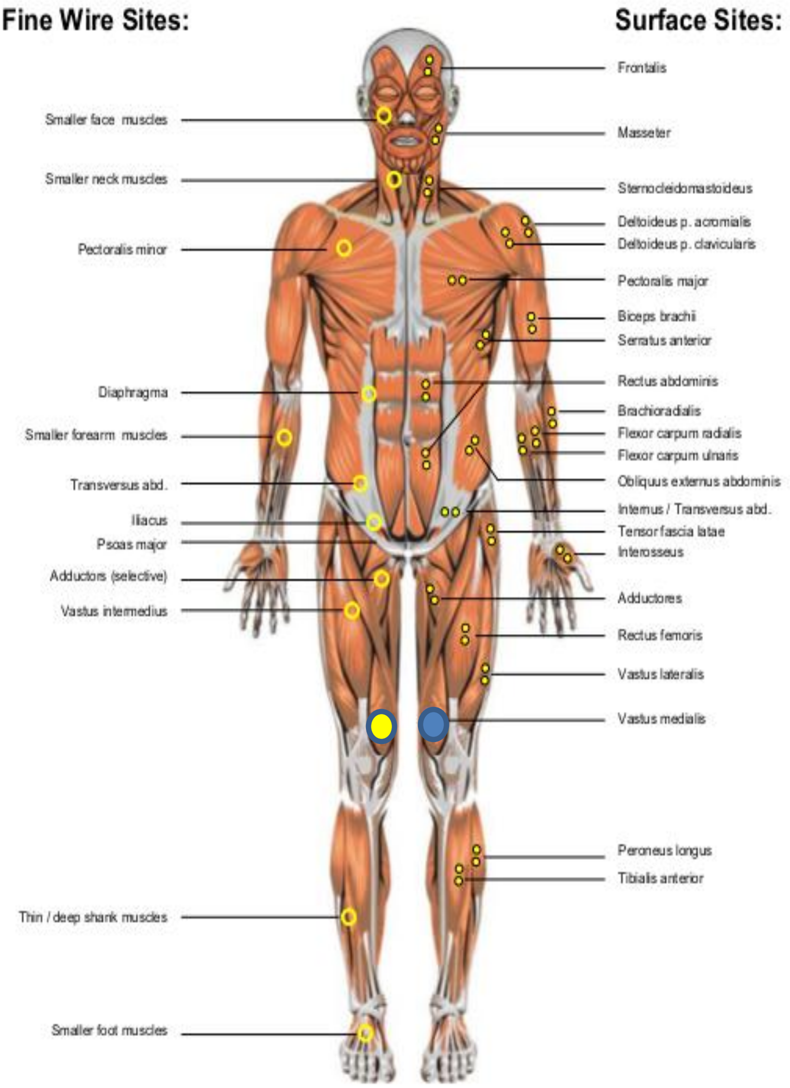


Figure 2.1: Anatomical positions of some electrode sites, frontal view. The right side indicates surface muscles and electrodes positions

- Sensor 1 located in Vastus medialis of the left leg
- Sensor 2 located in vastus medialis of the right leg

Table 2.1: Location of sensors 1 and 2 and muscles names

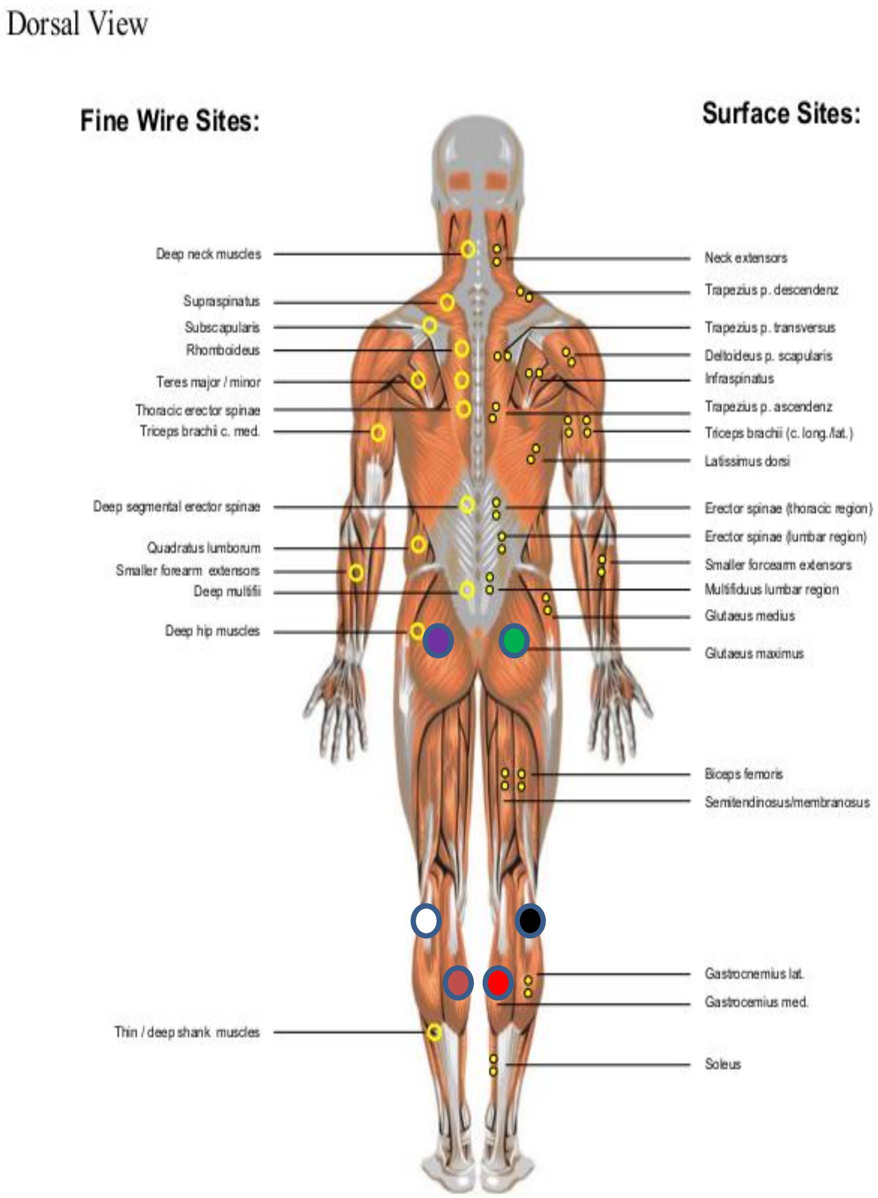


Figure 2.2: Anatomical positions of some electrode sites, dorsal view. The right side indicates surface muscles and electrodes positions

Sensor 3 located in gastrocnemius med of the left leg
Sensor 4 located in gastrocnemius med of the right leg
Sensor 5 located in gastrocnemius lat of the left leg
Sensor 6 located in gastrocnemius lat of the right leg
Sensor 7 located in gluteus maximus of the left leg
Sensor 8 located in gluteus maximus of the right leg

Table 2.2: Location of sensors 3-8 and muscles names

2.3 Reflecting markers

35 reflecting markers were located all over the body as we can see in the Figure 2.3. These markers are used to record the gait kinematics. As it has been said before, EMG signals and gait kinematics were recorded synchronously. The reflecting markers mark then which is the exact position of the part of the body where are located in a specific time instant and for a specific signal level. For example, we can find out where is located the right knee exactly when the level of the signal is maximum. It is just necessary to wee which is the position of RKNE marker in that moment.

For this thesis we focus the attention on the reflecting markers LHEE and RHEE, identified in the Figure 2.3 with pink circles. These two devices are very useful when segmenting the EMG signals by cycles, as it would be explained later. We should not lose sight of the markers LANK-RANK and LTOE-RTOE. Each one of these pairs is a good substitute of the pair LHEE-RHEE. When there is any problem with LHEE or RHEE one of the other pairs of markers can be used.

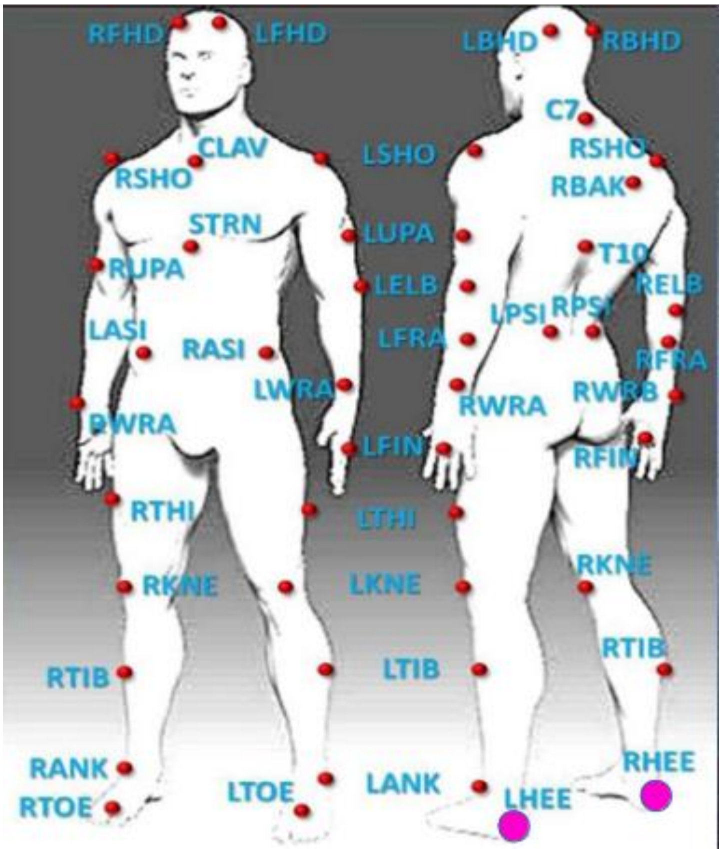


Figure 2.3: Reflecting markers positions

2.4 Aim of the thesis

Having many raw EMG records, obtained in the same similar conditions, we can get by signal averaging methods the objective model of EMG signal. This is the aim of this thesis.

The goal is to obtain one model for each muscle with the 2 Kg load held with each of the hands and with both hands. For example, we will obtain one model for the Sensor 2 with the load held with both hands. This is useful to understand the activity of the vastus medialis of the right leg during gait.

First we start by segmenting the signals by cycles. After that, it's time to normalize the signals to obtain signals with the same number of samples. Finally we calculate the average of the waveforms to obtain the final models.

All this steps are widely explained in the Chapter 3.

Chapter 3

Methodology

Once explained the background it is time to talk about the methodology used to develop the thesis. The methodology followed consists in a series of steps to obtain the final models desired from the EMG signals and kinematics records result of background. The steps followed are segmentation, normalization and calculation of the averages. Once we complete these steps we can obtain the final models we are looking for.

The segmentation and the normalization can be considered as a preprocessing of the signals. That is because it consists in preparing the data in a way that facilitates the calculation of the averages. With the calculation of the averages the final models will be obtained. This calculation will be considered then the real processing of the signals.

3.1 Segmentation

The first thing you should do in EMG signals preprocessing is to separate the different cycles existing in measures. Our ambition is to obtain a model comparing all the cycles so firstly it is necessary to separate them.

3.1.1 What is a cycle?

A cycle is defined in our context as an EMG signal segment that starts when the position of the LHEE marker regarding to the human gait direction and the position of the RHEE marker regarding to the same direction have the same value and ends when these two markers have the same value for a second time without counting the time that marks the beginning of the segment.

Once explained this technical and incomprehensible definition, let’s try to understand its meaning. Cycle concept is really easy. It is just the segment of EMG signal that starts when the feet are crossed and that ends when they are crossed again after stepping with both feet.

The name "cycle" is used in this case because this process is repeated in a cyclic way. In fact, this is the aim of the segmentation. Obtaining many different samples of the same process helps to create an objective model of this process.

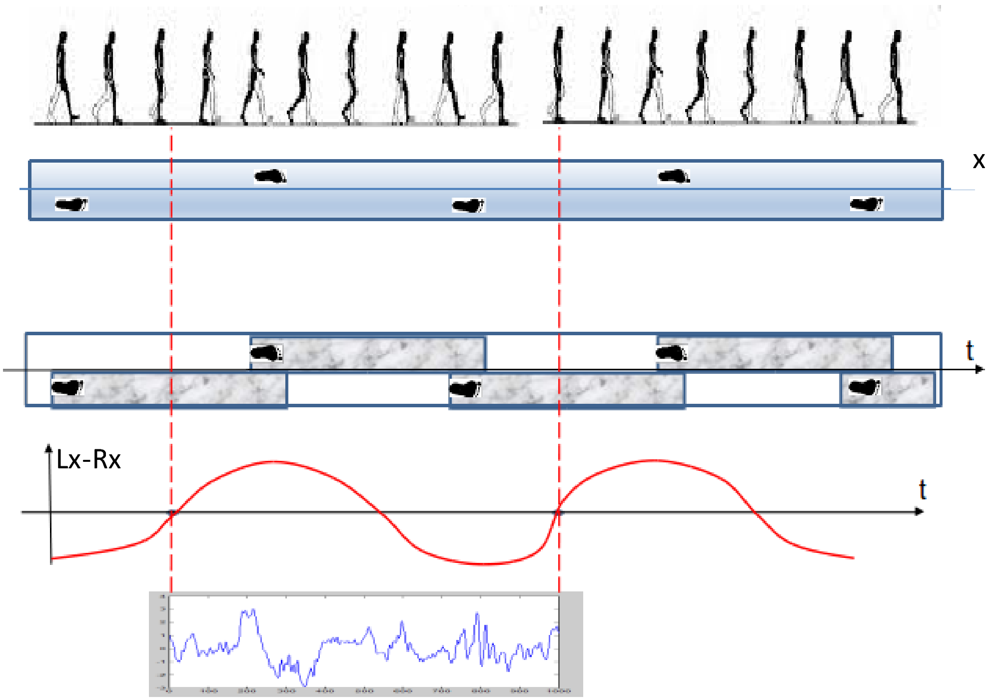


Figure 3.1: Cycle explanation

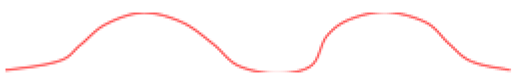
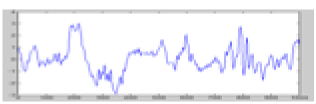
	Right footprint	t	Time
	Left footprint	x	Distance
	Foot is touching the floor		
Lx	Position of left foot in x axis		
Rx	Position of the right foot in x axis		
Path signal			
Cycle			

Table 3.1: Figure 3.1 explanation

The best way to understand this concept is in a graphic way. In the Figure 3.1 an explanation of cycles is shown. On the top of the Figure 3.1 an example of human gait appears. With this illustration now it is clear when the cycle starts and ends. The cycle starts with the first red dotted line and finishes with the second one.

It is evident that the point in which both feet are crossed is almost the medium point between left and right 'footprints'. In this point LHEE and RHEE have the same value of x (LHEEx = RHEEx).

The red signal, named path signal, will be discussed later, but it is obvious that it is a periodic signal. It means that the process that generates this signal is cyclic. In the bottom of the Figure 3.1the cycle can be seen. This cycle will be very useful to create the objective model we are looking for.

3.1.2 Path signal

This name has been chosen because this kind of signal changes its level depending on the path followed by the tested person. There is an example of a path signal in the Figure 3.1.

The path signal shows the difference between the position of the left foot regarding to the direction of the gait and the position of the right foot regarding to the same direction in a concrete instant of time. LHEE and RHEE markers are used to locate the left foot and the right foot respectively. It is enough to see the position of each foot in the stationary path used for the experiment. With the use of cameras and the reflective markers it is not complicated.

As it can be seen in the Figure 3.1 the path signal is a periodic signal. This is easy to explain. The cycle starts when both feet have the same position, so the value of the path signal must be 0. After that the signal increases or decreases its value depending on which foot is moving, describing a sine. When both feet are touching the floor the value of the signal is maximum or minimum, depending on which foot has the higher position. This process is always repeated because the tested person walked by a stationary path without changing the gait. So with the kinematic records we obtain a lot of path signals and consequently a lot of cycles.

3.1.3 Cycles extraction

Now that the cycle and the path signals are explained it is time to talk about the methodology used to extract the cycles from the complete EMG signals. As it is known this process is called segmentation.

Firstly it has to be said that this process is started with 7 different measures for the 2 Kg load held with the left hand, 4 measures for the load held with the right hand and 6 measures in the case of holding a 2 Kg load with each hand. It must be remembered that each measure should contain many different cycles so now it is turn to proceed with the segmentation.

In these measures there is information about the position of all of the reflecting markers regarding to the stationary path. Then we select the position of the LHEE and RHEE markers that are the subjects of interest. The position of the markers is expressed in mm and the sampling frequency of the camera is 100 Hz, so there are 100 position samples by second. Sometimes this information is not available due to problems with the markers. In that case the pair of markers LANK-RANK or the pair LTOE-RTOE is chosen. These pairs are located in the feet too so they are suitable for our purpose. However, from this moment, in this document only the LHEE and RHEE names will appear. The reader should not be distracted.

Now that the information of interest has been selected it is time to create the path signals. It is just necessary with creating a vector containing the difference between the LHEE position and the RHEE position. Always we do LHEE-RHEE, never RHEE-LHEE.

With this vector now it is very easy to separate it into smaller vectors corresponding to a sine each of them. It is just necessary to see in which position of the vector a change of sign is produced (+ to - or - to +). To decide which change of sign is searched it becomes necessary to check the evolution of the position of any of the two markers studied over time.

If the position increases over time as in the example of the Figure 3.2 the change of sign searched is from the - sign to the + sign. On the other hand, if the position decreases over time as in the Figure 3.3 the change of sign searched would be form + to -.

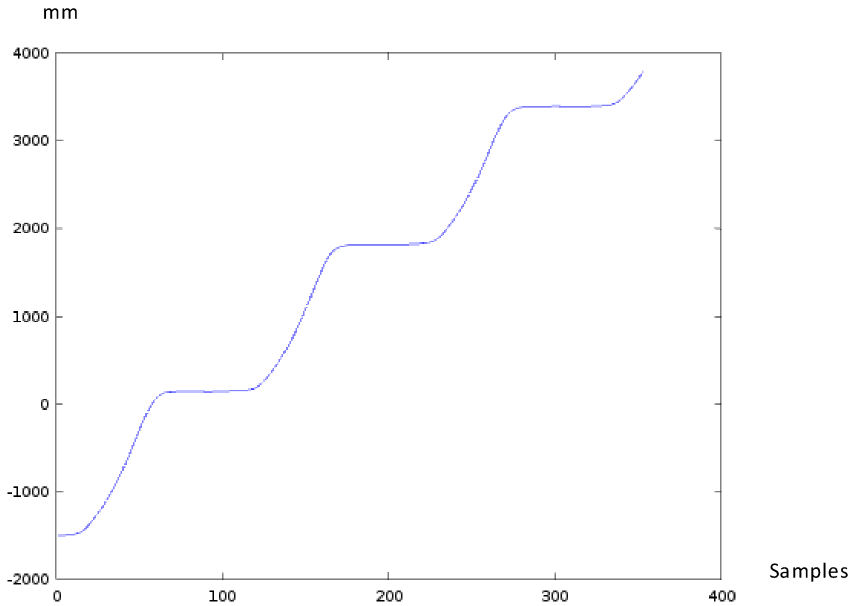


Figure 3.2: Position of left foot during the time corresponding to a measure with the load held with both hands, with positive displacement

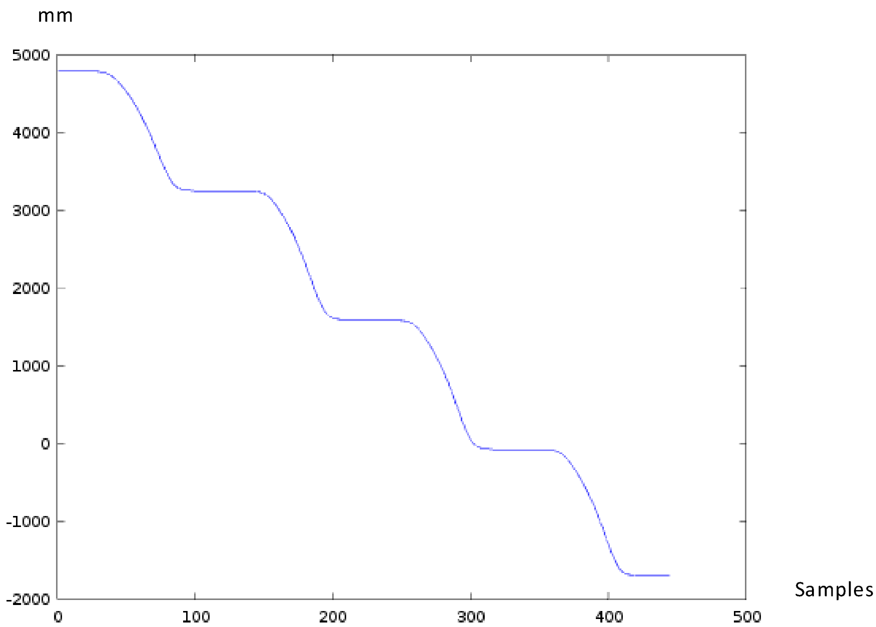


Figure 3.3: Position of left foot during the time corresponding to a measure with the load held with left hand, with negative displacement

The reason to choose one change of sign or the other is that the tested person sometimes walked from the left side to the right side of the stationary path. Then, sometimes the position of the feet were increasing and sometimes decreasing. We must adjust it like that because later we will like to obtain EMG cycles that start when left foot starts moving after both feet were crossed.

With this change of sign found starts a cycle. The end of the sine arrives when the same change of sign is produced. This process is repeated until there are not more cycles. In the Figure 3.4 it is possible to see the original path signal (whole vector) and in the Figure 3.5 one separated cycle (extraction of the original vector).

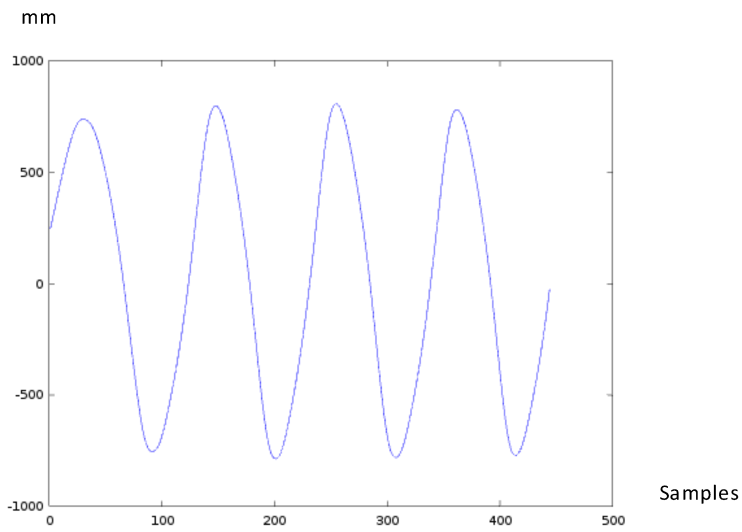


Figure 3.4: Complete path signal from a measure

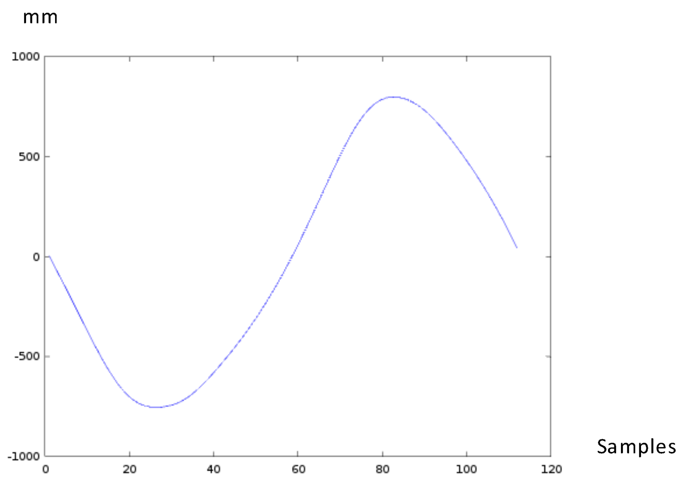


Figure 3.5: Cycle extracted from the signal of Figure 3.4

As it can be seen, in this measure the tested person walked from high positions to lower positions, that's why the signal has this form.

3.2 Normalization

The next step to be followed is the normalization of the EMG cycles obtained previously. The aim of the normalization is just to adjust cycles to make them have the same number of samples.

Cycles do not have the same number of samples. However, the length is very similar. This small difference is caused by the "irregularity" in human gait. A human does not use always the same time to give a step. Nevertheless the duration is almost the same. For this reason the number of samples for each cycle is different.

All the cycles obtained for the elaboration of this thesis have a number of samples bigger than 1000 but near this number (1040, 1060…). Then, 1000 is the chosen number for our purpose.

Why the normalization is needed? After the normalization the normalized cycles will be processed to obtain averages. It is very useful then to have all the cycles with the same number of samples.

3.2.1 Signal spectrum

Firstly it is necessary to obtain the spectrum of the signal (cycle). That means obtaining the frequency components of the signal. The FFT (Fast Fourier Transform) is used for this purpose.

In the Figure 3.6 and Figure 3.7 we can see that the EMG cycle and its FFT have the same length, 1070 samples. It can be also seen that almost all the spectral content is located in the left side and in the right side. The values for the central points are very low. These points correspond with the higher frequencies of the signal. This situation is the same for all the EMG cycles. It is not an isolated case.

It is possible to delete the values of the central points of the Figure 3.7. The information lost is related with very high frequencies and with very low values, so this information is not very important. The purpose of the thesis is not affected by erasing this data. Then, if the cycle has 1000 + x samples, the FFT is obtained and the x central points of this FFT are discarded, as it can be seen in Figure 3.8.

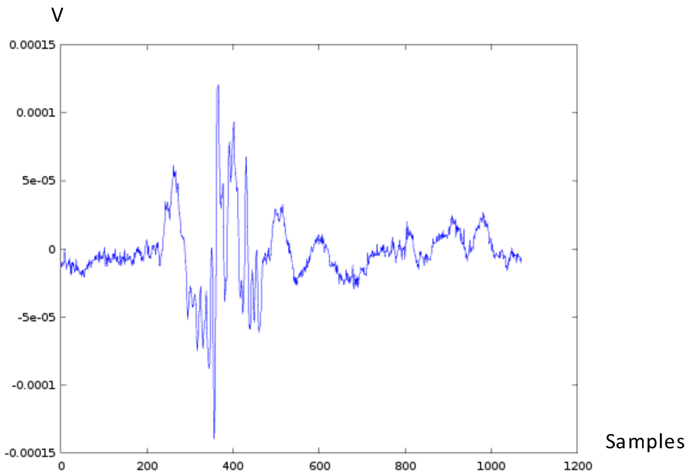


Figure 3.6: Example of EMG cycle

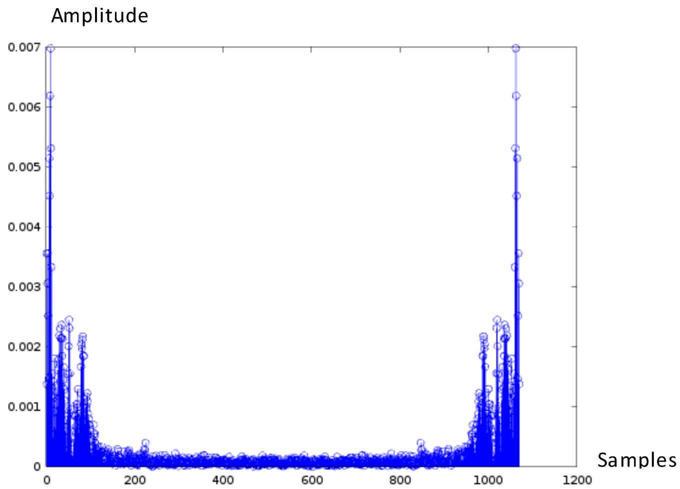


Figure 3.7: FFT of Figure 3.6

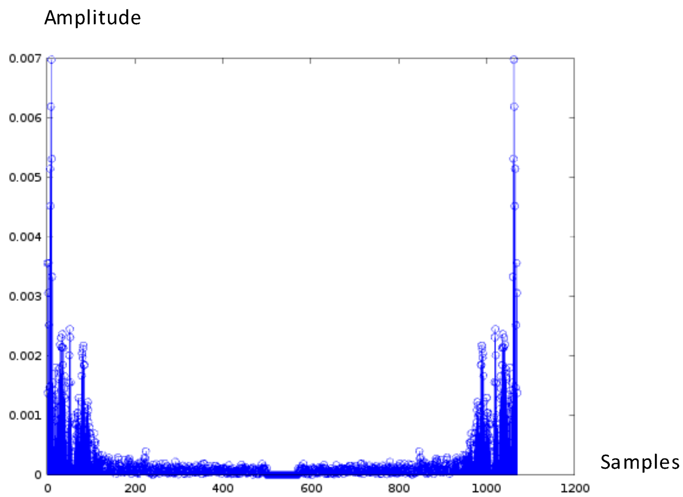


Figure 3.8: FFT of Figure 3.6 without the 70 central values

3.2.2 Signal reconstruction

Now it is the moment to reconstruct the signal. The IFFT (Inverse Fast Fourier Transform) is used for that. The IFFT transforms the spectrum back again into a temporal signal.

The IFFT is the inverse process to the FFT. Then, we obtain for the temporal signal the same points as the spectrum. So when we do this inversion from the frequency to the time we obtain a 1000 samples length temporal signal.

In the Figures from 3.9 to 3.12 a comparative between the original EMG cycles and the reconstructed ones can be seen. The original EMG cycles have an irregular number of samples, larger than 1000. The reconstructed ones have 1000 samples. Now it would be easy operate with them.

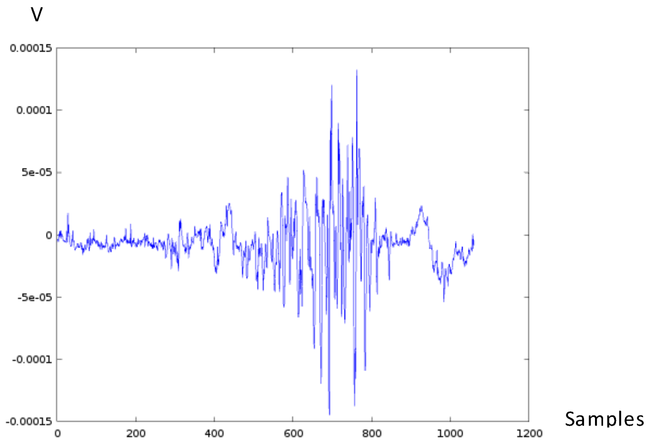


Figure 3.9: Original EMG cycle corresponding to a measure of the sensor 4 with the load held with both hands

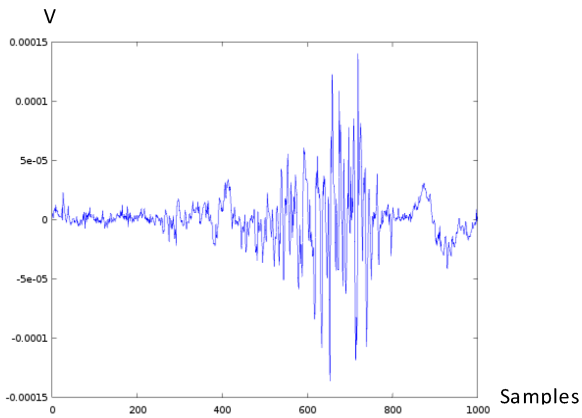


Figure 3.10: Cycle of Figure 3.9 normalized

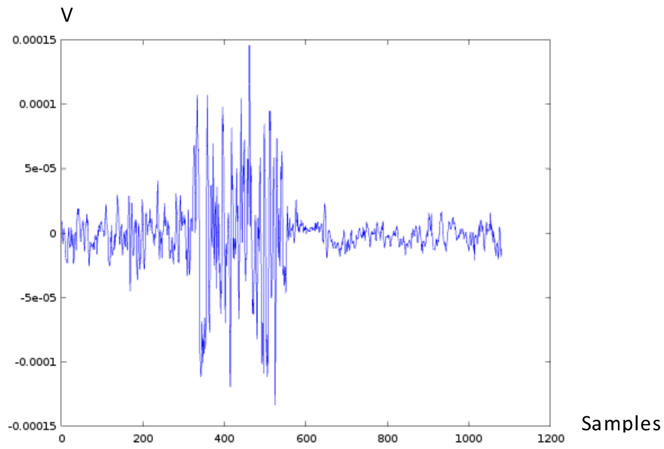


Figure 3.11: Original EMG cycle corresponding to a measure of the sensor 5 with the load held with the right hand

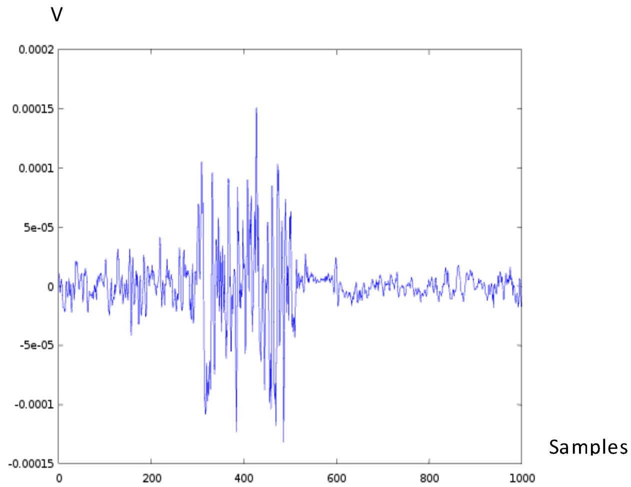


Figure 3.12: Cycle of Figure 3.11 normalized

It can be seen that there is almost no difference between an original EMG signal and the reconstructed one. This is possible because the change produced to the signal is a minimum change.

In our case the number of samples is always near to 1000 samples. The number of points that must be erased is very low. Then, only very high frequencies disappear. There is no useful information in very high frequencies, so it is not a problem.

However, in the Figures 3.13 and 3.14 we can see what happens if more points of the FFT are removed. It results evident that when more points are eliminated lower frequencies start to be affected. If frequencies with a lot of weight in the signal become affected the waveform changes and it can be appreciated by humans.

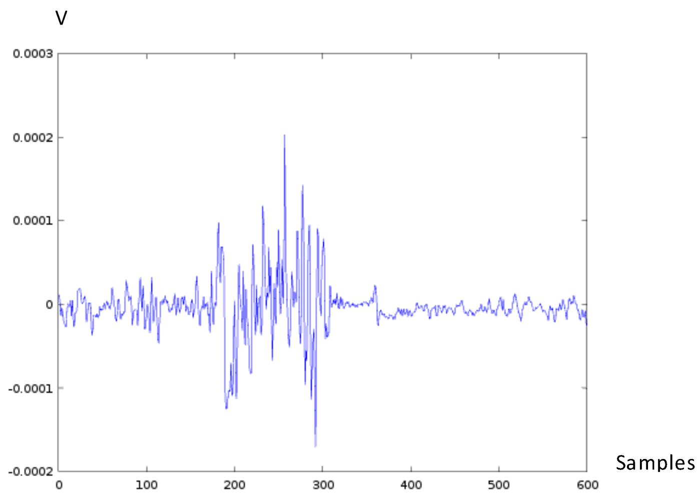


Figure 3.13: Normalization of the cycle of Figure 3.11 to 600 samples

In the Figure 3.13 it is evident that the signal appearing is not the same as the one of the Figure 3.11. More than 400 samples have been eliminated. Relevant information about the signal has been removed. Some important frequencies for the EMG signal are not being considered. Nevertheless, the waveforms of both figures are relatively similar. That confirms that the most important information of the signals is located in "low" frequencies.

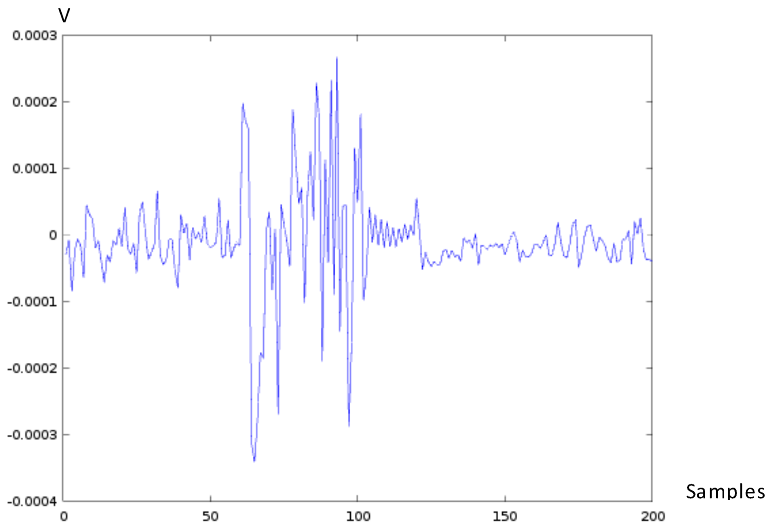


Figure 3.14: Normalization of the cycle of Figure 3.11 to 200 samples

In the Figure 3.14 more than 800 samples have been removed. Now results very difficult to establish a relationship between this signal and the signal of the Figure 3.11. A lot of information has disappeared and the reconstructed signal has almost no relation with the original one.

3.3 Artifact removal

An artifact is an undesirable variation of the voltage. This phenomenon can be produced by different factors. For example, if an electrode is disconnected, interferences with other machines…

These artifacts must not be in the normalized cycle, because it will be used to obtain a model. Then, it becomes necessary to remove the artifacts appearing in some of the cycles.

In the figure it is seen a cycle with an artifact marked with an ellipse. It would be enough with observing in which positions appear this artifact and put them a null value. This way is very fast and easy and it is enough for our aim. In the figure the same cycle without the artifact is shown. If the artifacts are not removed, they will affect negatively when obtaining averages, because of his very high or low value.

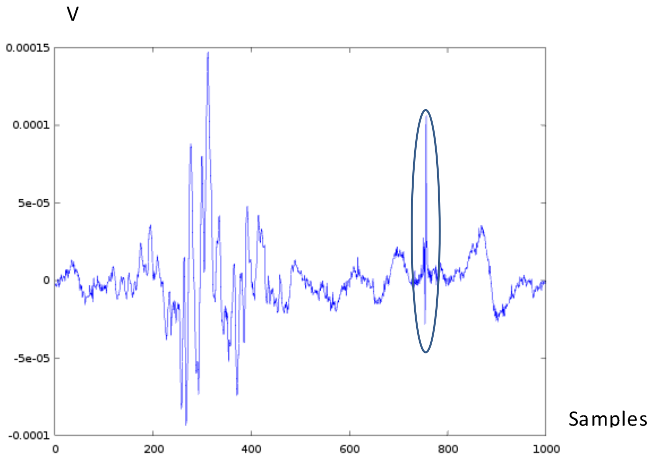


Figure 3.15: EMG cycle with artifact

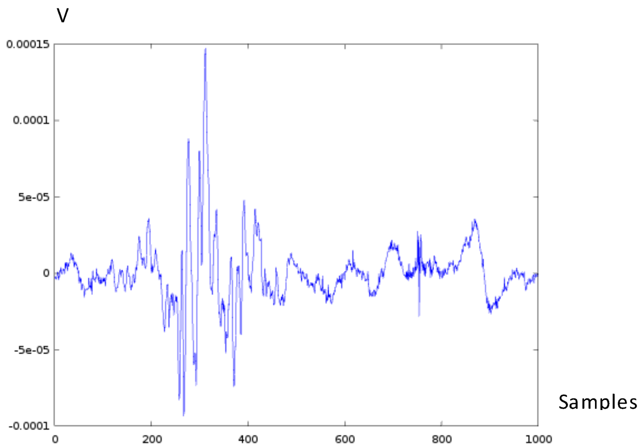


Figure 3.16: Cycle of Figure 3.15 without artifact

3.4 Calculation of the average

Once the preprocessing has finished and the EMG cycles have been segmented and normalized it is time to start with the real processing of the signals.

The aim of this thesis is to obtain objectives models about EMG signals. The way to obtain these models is to compare the different cycles and obtain averages to highlight the common points of the related cycles and remove peculiarities of some cycles.

Two different kinds of average are going to be used. A simple arithmetic average is used first and then a correlated average is applied. Later the results of both averages will be discussed to see which one is more useful for our purpose.

3.4.1 Arithmetic mean

Firstly, let's provide a technical definition of the arithmetic mean:

"*The arithmetic mean (or mean or average) is the most commonly used and readily understood measure of central tendency. In statistics, the term average refers to any of the measures of central tendency. The arithmetic mean is defined as being equal to the sum of the numerical values of each and every observation divided by the total number of observations. Symbolically, if we have a data set containing the values $a_1,\ldots,a_n$. The arithmetic mean A is defined by the formula*

$$A = \frac{1}{n}\sum_{i=1}^{n} a_i = \frac{a_1 + a_2 + \cdots + a_n}{n}$$

"

So for this thesis we are going to create an arithmetic mean for each sensor and for the 2 Kg load held with the left hand, with the right hands, and with both hands. For example, one arithmetic mean is made with all the cycles corresponding to the sensor 2 and with the load held with the left hand, as we can see in the Figure 3.17. Some other examples are shown in the Figures from 3.18 to 3.22.

It is very easy to apply the arithmetic mean because now all the cycles have the same length. Then, it is just necessary to apply the formula to the values of the cycles located in the same position (same number of sample) and like that the mean value searched for this position is found.

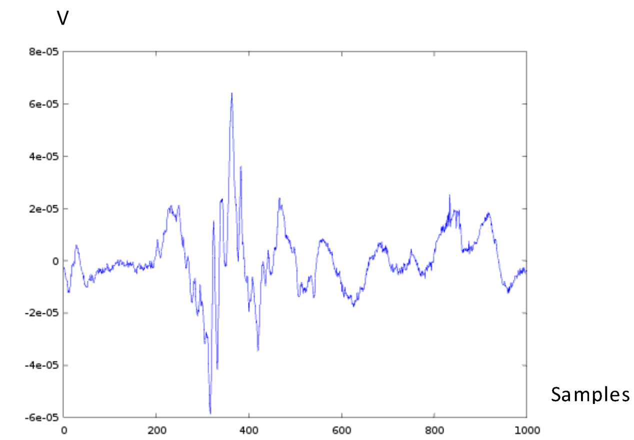


Figure 3.17: Arithmetic mean of cycles from sensor 2. Load in the left hand

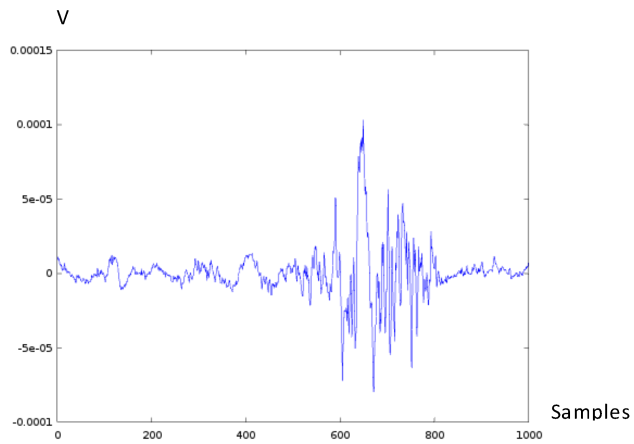


Figure 3.18: Arithmetic mean of cycles from sensor 4. Load in the left hand

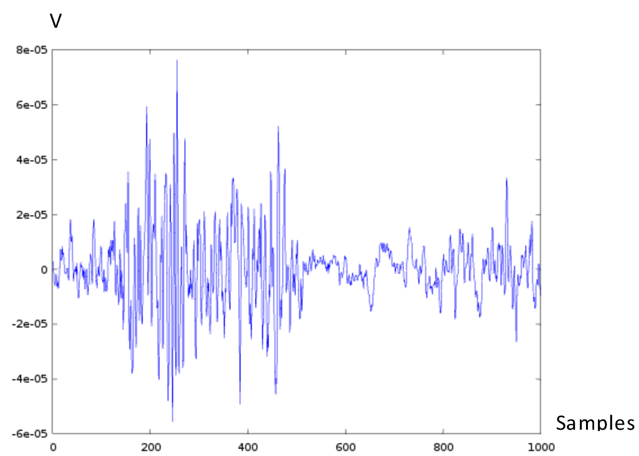


Figure 3.19: Arithmetic mean of cycles from sensor 5. Load in the right hand

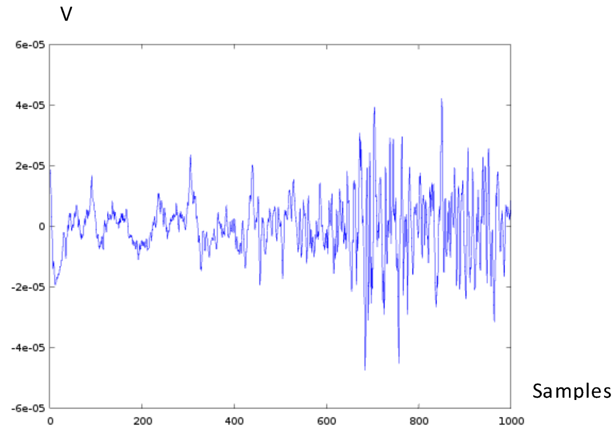


Figure 3.20: Arithmetic mean of cycles from sensor 6. Load in the right hand

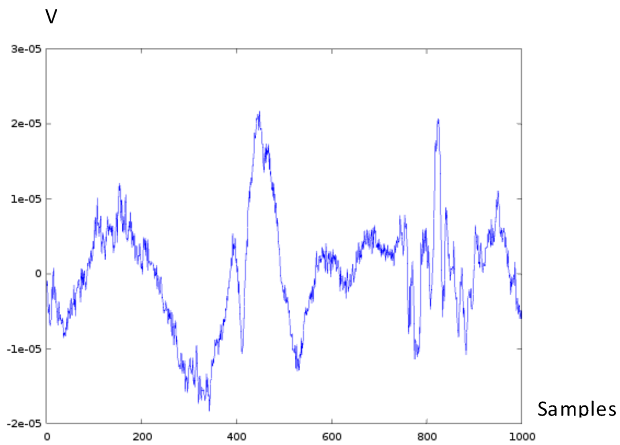


Figure 3.21: Arithmetic mean of cycles from sensor 7. Load in both hands

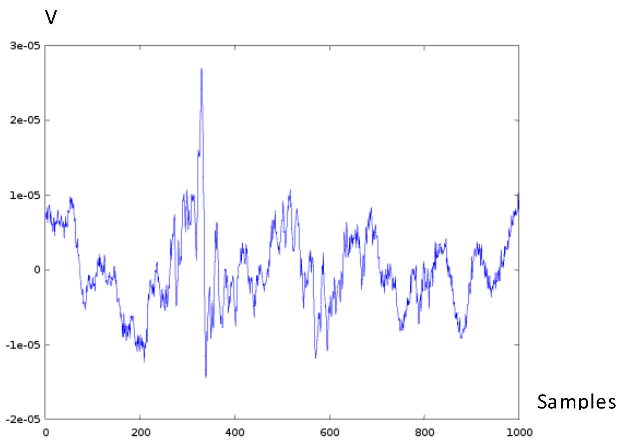


Figure 3.22: Arithmetic mean of cycles from sensor 8. Load in both hands

In these Figures from 3.17 to 3.22 it is shown that the EMG signals, arithmetic means in this case, are very different depending on the sensor. The muscles studied by each sensor are different so their activity is different too.

In the Figure 3.23 we find a comparative between a simple EMG normalized cycle and the arithmetic mean in which it takes part. As it can be seen the irregularity of the simple EMG signal almost disappears in the mean and the important information that describes the real muscular activity searched highlights more. We know it is the important information because it appears in all the cycles that take part in the mean. This common activity is what is searched, because it is the useful information to create objective models.

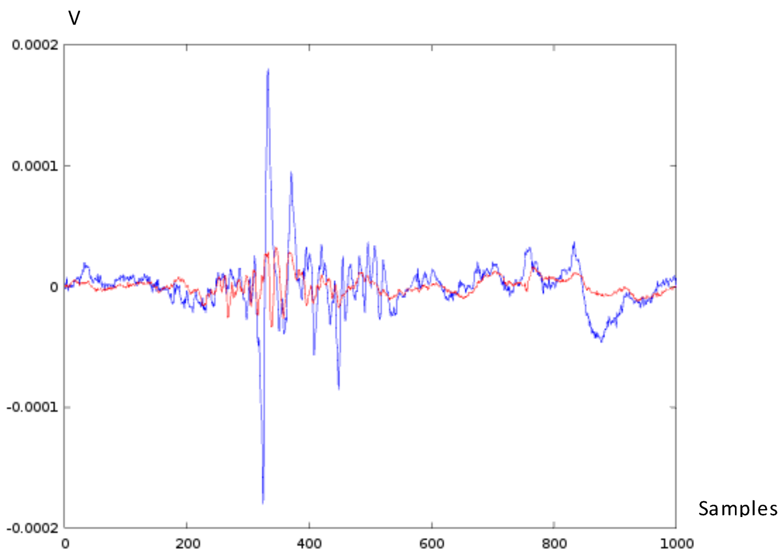


Figure 3.23: In red, arithmetic mean for sensor 2. Load in left hand. In blue, simple EMG cycle taking part in the mean

However, it results evident that although the irregularity of the right of the signal disappears, the level of the signal decreases considerably in the mean. This is due to the displacement from one signals respect other signals in the same mean. The synchronization is a complex process and sometimes a perfect result in not possible. The beginning of muscular activity is not always produced in the same instant. These displacements between signals produce cancellations when calculating the mean so the level of the final signal is affected and has a lower level.

To find a solution to this problem another kind of average is used. The correlated average is selected. This average is explained in the next point.

3.4.2 Correlated average

The purpose of the use of this average is to solve the problem of the signals displacements. The idea is to realize a simple mean but with the cycles relocated in a way in which the level of the important information of the signal is not affected by cancellations. If this goal is reached we will obtain a similar signal to the simple mean but with higher level for the important values.

Which is the process followed to obtain the correlated average? The process is more complex than the used for the arithmetic mean. Now, it is not possible to obtain the mean "combining" all the cycles in once. Now it is necessary to step by step, cycle by cycle.

Let's explain this. As it is known, it is wanted to obtain a higher level of the final average by manipulating cycles. How can this purpose be accomplished? It is easy. Correlation coefficient is going to be used to see how much the cycle should be displaced.

Specifically, the coefficient used is the Pearson product-moment correlation coefficient. This coefficient (ρ) is a measure of the linear correlation between two variables X and Y, giving a value between +1 and -1 inclusive, where 1 is total positive correlation, 0 is no correlation, and -1 is total negative correlation. In the Figure 3.24 we find some examples for different values of ρ.

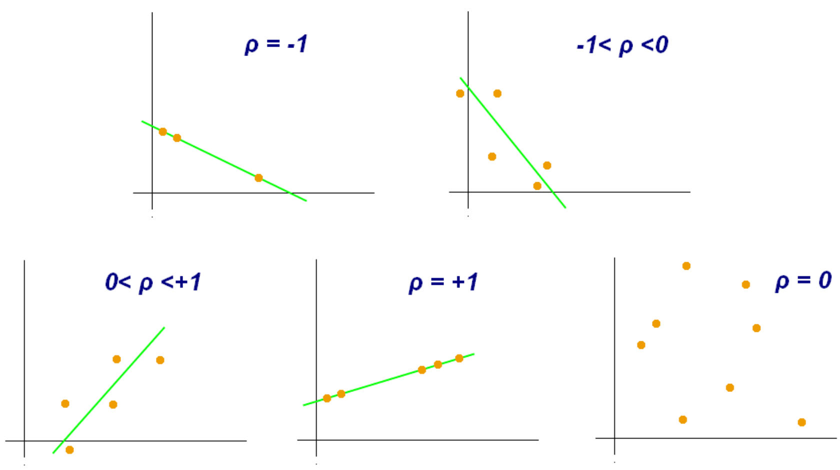


Figure 3.24: Examples of scatter diagrams with different values of ρ

Essentially, for this thesis, this coefficient indicates how similar two signals are.

Now that the correlation coefficient concept has been introduced let's continue with the explanation. This coefficient provides us a tool very useful for our purpose. Right now it is just enough to displace one signal over another while we calculate the correlation coefficient. Later, the displacement who has the highest coefficient is the chosen one. We calculate the average with the displaced signal. Then, we will repeat the process for every cycle with the average cumulative until the moment.

As well as for arithmetic means, we are going to create an arithmetic mean for each sensor and for the 2 Kg load held with the left hand, with the right hands, and with both hands.

It is very difficult to understand this process if it is not explained in a graphic way. Let's try then to explain it with some images. The Figures from 3.25 and 3.26 represent the complete process followed to obtain the correlated average for the Sensor 2 with the 2 Kg held with the left hand. There are 8 cycles in total.

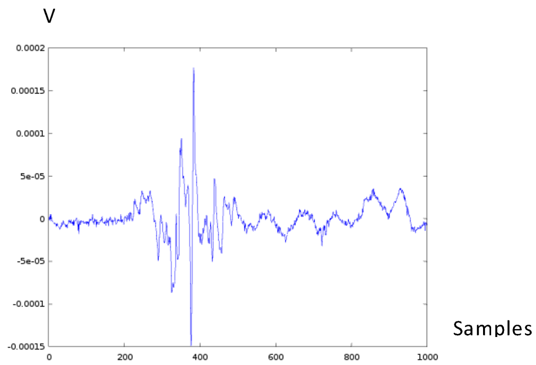


Figure 3.25: EMG cycle of sensor 2. Load held with left hand

As we see in the Figure 3.25 firstly we choose one random cycle. To make it easy the chosen one will be the first one obtained in normalization.

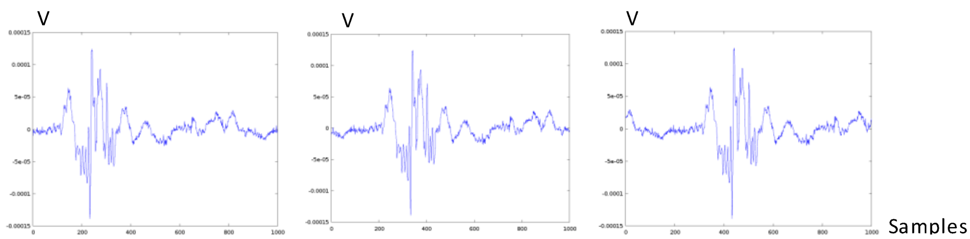


Figure 3.26: Central signal; Another EMG cycle of sensor 2. Load held with left hand. The other signals are displacements of the first to both sides.

In Figure 3.26 we see that next step consists in taking the next cycle and to displace it from 100 samples to the left to 100 samples to the right, passing by the original position. The number 100 it is selected because it is big enough to contain the signal with the biggest correlation coefficient with the previous signal.

For each of these positions we obtain the Pearson product-moment correlation coefficient with the signal of Figure 3.25. Then we choose the position with the biggest coefficient value, the nearest to 1. Now we obtain a simple mean between the signal of Figure and the signal of Figure 3.26 displaced to the position that makes it have the biggest correlative coefficient.

This process will be repeated until all the cycles are included in the average. Once we have the first average, the one explained previously, now we will take this average as it was the signal of Figure 3.25. The third cycle will replace now the cycle of Figure 3.26. However, every cycle must have the same weight in the average. Then, the algorithm used is the following:

This algorithm must be used until there are not more cycles. The n is the index of the cycle that is being included into the mean. If there are more cycles left, the mean will be the cumulative mean for the next signal.

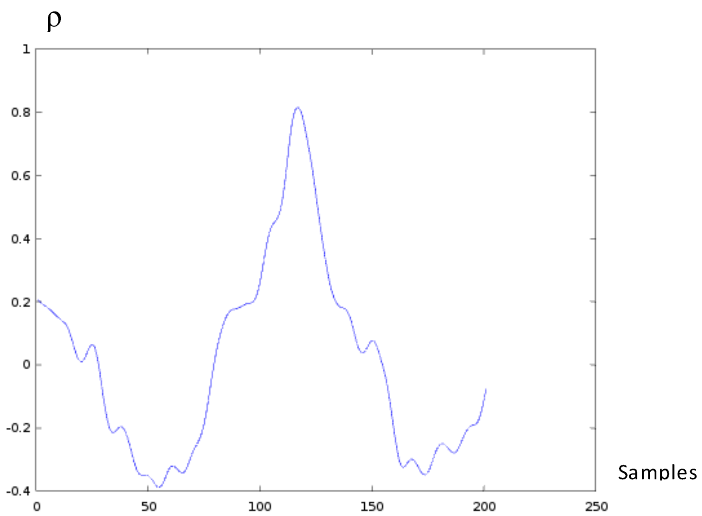


Figure 3.27: ρ for the different displacement of the third cycle of sensor 2 with the load in the left hand over the mean of the first and second cycles

For example in Figure 3.27 it can be seen the correlation coefficients when the third cycle of the sensor 2 with the load held with the left hand is displaced over the mean of the first and second cycles. The maximum is more or less 0.8, and it is located in the sample 120. The sample 100 represents no displacement of the signal. Previous samples represent the displacement of the signal to the left side, and the other samples to the right side. In this case the signal must be displaced 20 samples to the right before calculating the mean.

When all the process is finished and all the cycles are included we obtain finally the correlated average. In the figures some examples of these averages can be found.

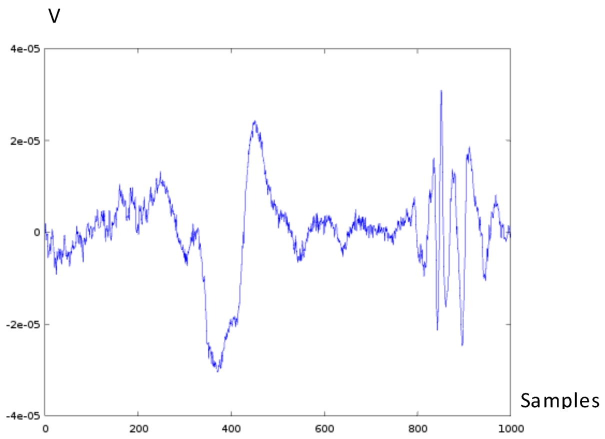


Figure 3.28: Correlated average of cycles from sensor 7. Load in the left hand

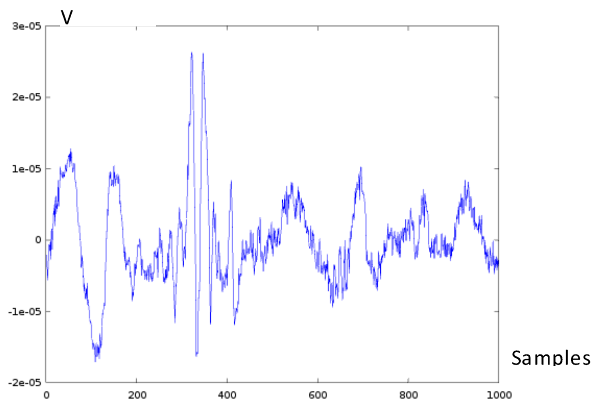


Figure 3.29: Arithmetic mean of cycles from sensor 8. Load in the left hand

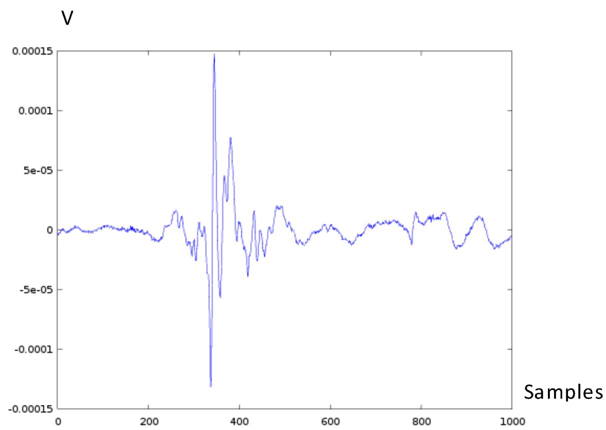


Figure 3.30: Arithmetic mean of cycles from sensor 2. Load in both hands

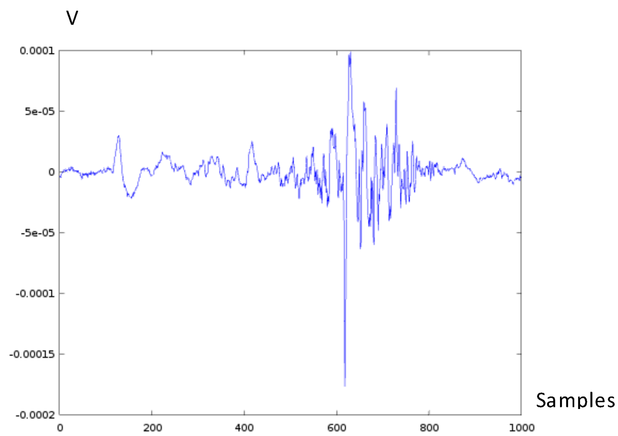


Figure 3.31: Arithmetic mean of cycles from sensor 4. Load both hands

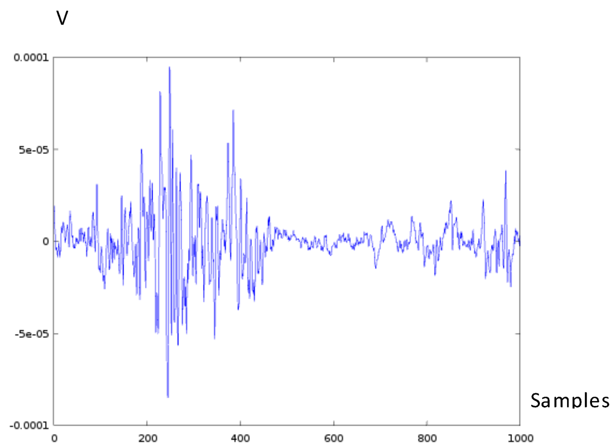


Figure 3.32: Arithmetic mean of cycles from sensor 5. Load in the right hand

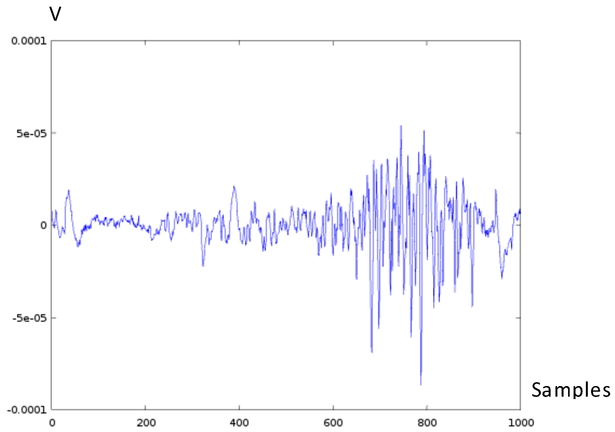


Figure 3.33: Arithmetic mean of cycles from sensor 6. Load in the right hand

In Figures from 3.28 to 3.33 it is seen that the results obtained are similar to the obtained with the arithmetic mean. However, there is an appreciable difference. This will be discussed later.

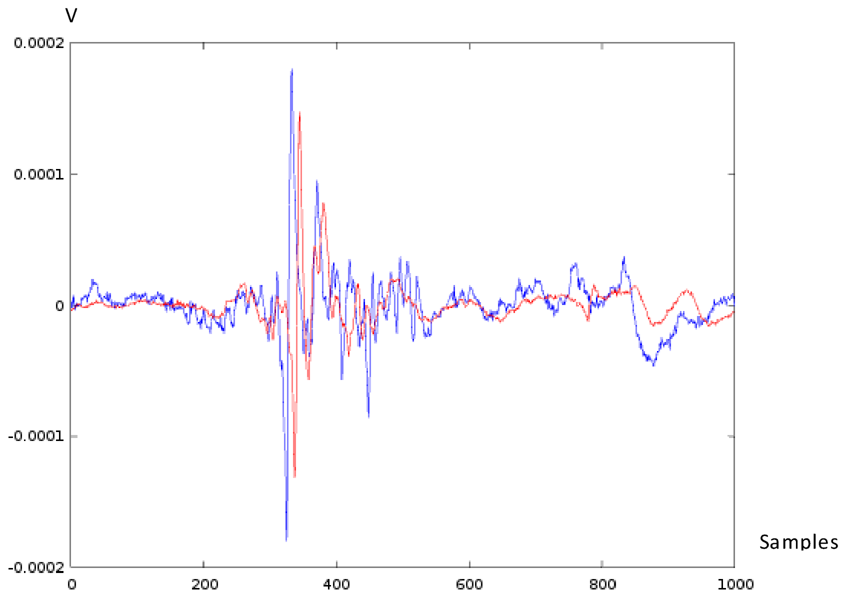


Figure 3.34: In red, correlated average for sensor 2. Load in left hand. In blue, simple EMG cycle taking part in the mean

As it was done in the arithmetic mean section, in the Figure 3.34 there is a comparative between a simple EMG normalized cycle and the correlated average in which it is used. The cycle used it is the same as in Figure 3.23. Like that, the difference between using the arithmetic mean or the correlated average it is shown. As it can be seen not only the irregularity disappears. Now, the level of the important part of the signal is higher than in the arithmetic mean.

Now we have finish with the processing. The objective models that were the aim of this thesis have been obtained. Let's analyze now the models.

Chapter 4

Discussion and conclusions

Now that the objective models have been obtained it is time to discuss the results obtained and reach some conclusions. Firstly, a comparative between the simple mean and the correlated average will be shown. After that, a deep spectral analysis will be explained.

4.1 Mean and correlative average comparative

First of all, let's take a look at the Figures from 4.1 to 4.4. Some comparatives between the simple mean and the correlative average are shown.

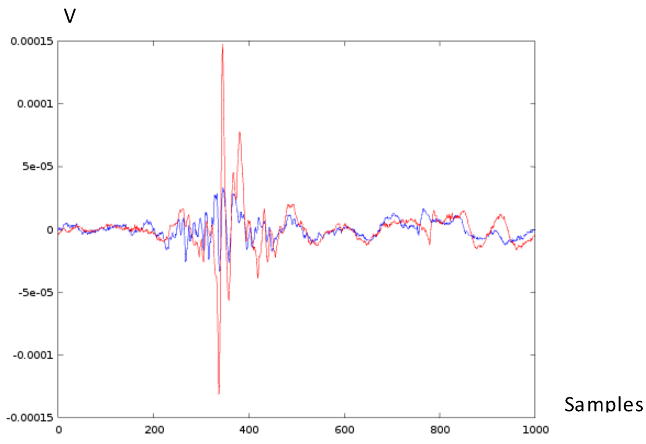


Figure 4.1: In red, correlated average for sensor 2. Load in left hand. In blue, the arithmetic mean

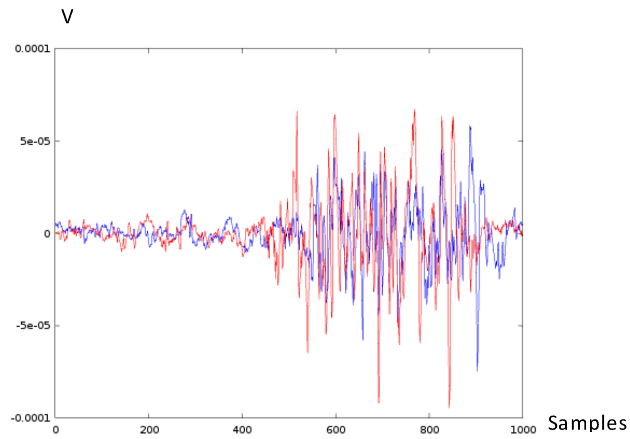


Figure 4.2: In red, correlated average for sensor 4. Load in right hand. In blue, the arithmetic mean

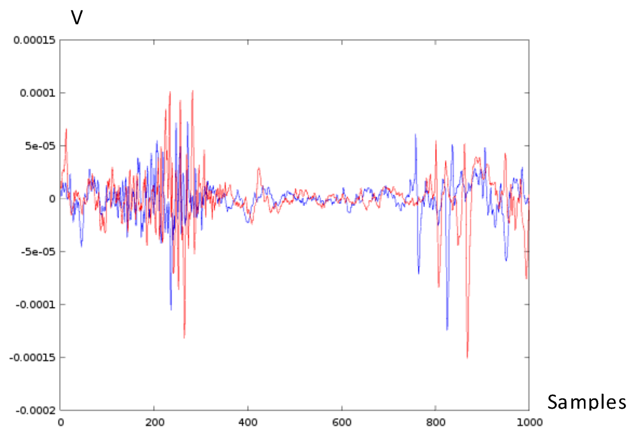


Figure 4.3: In red, correlated average for sensor 5. Load in both hands. In blue, the arithmetic mean

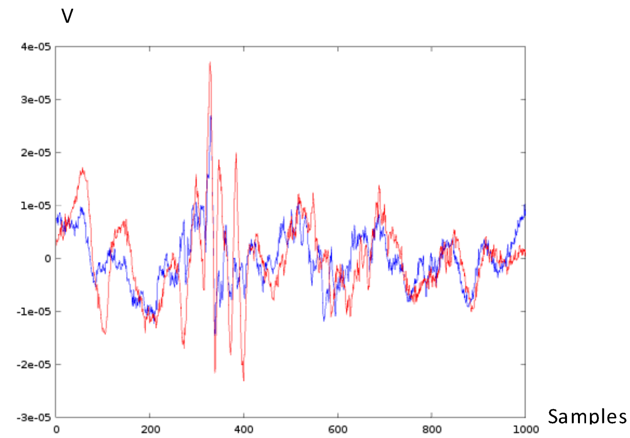


Figure 4.4: In red, correlated average for sensor 8. Load in both hands. In blue, the arithmetic mean

With these examples it results evident that the red colored signals represent a better model for each corresponding case. These signals correspond to the correlated averages. It is confirmed then that this method to obtain the average is better than the simple arithmetic mean.

It is true that the improvement has not unimaginable dimensions. However, this improvement can be appreciated by humans easily, what it shows that it is an important advance in obtaining the models.

Now let's realize a spectral analysis about the models obtained.

4.2 Spectral analysis

4.2.1 Averages comparative

To make it more understandable let's explain this analysis with a concrete example. Let's develop the example of the Figure 4.1. First of all the frequency components must be obtained as in the normalization. The FFT will be used again to provide the components. After, selecting the appropriated frequency components, 4 frequency bands are will be distinguished. The first band will correspond to 1-15 Hz, the second one to 16-40 Hz, the third one to 41-100 Hz and the last one to 101-500 Hz.

In the Figure 4.5 it can be seen an example of the FFT (spectrum) corresponding to a study of the first band of a signal. There are only components for the lowest frequencies (1-16 Hz).

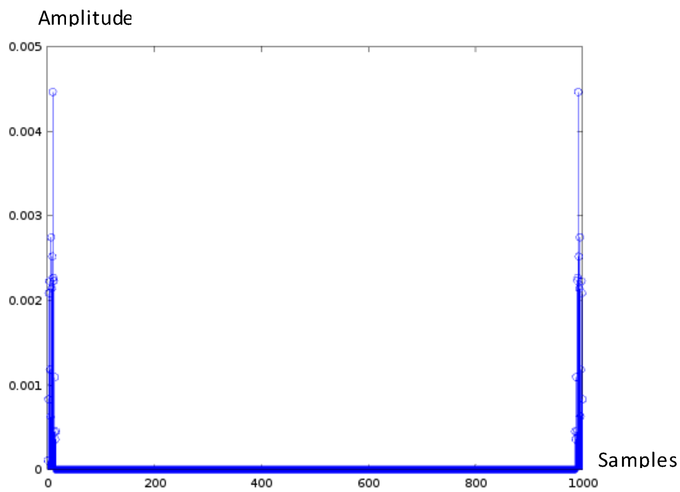


Figure 4.5: Example of FFT of a signal from the first band

In the Figure 4.6 and 4.7 it is shown in blue how are the signals corresponding to the first frequency band. It is evident that they correspond to the lowest frequencies of the signals in red.

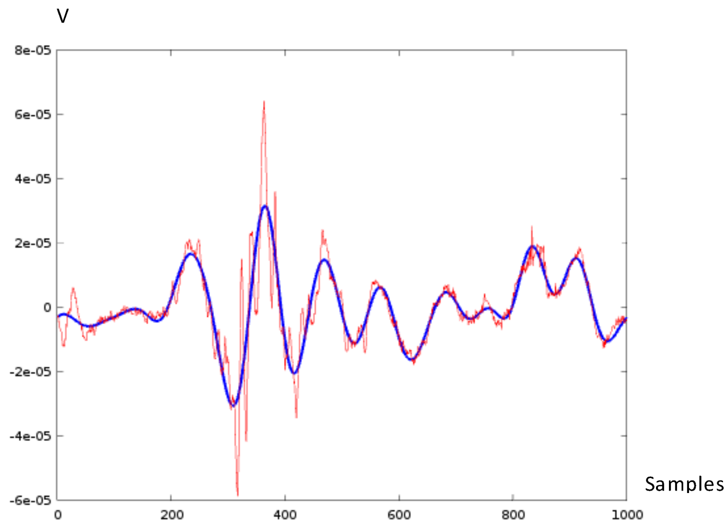


Figure 4.6: In red, arithmetic mean for sensor 2. Load in left hand. In blue, the first band of the signal in red

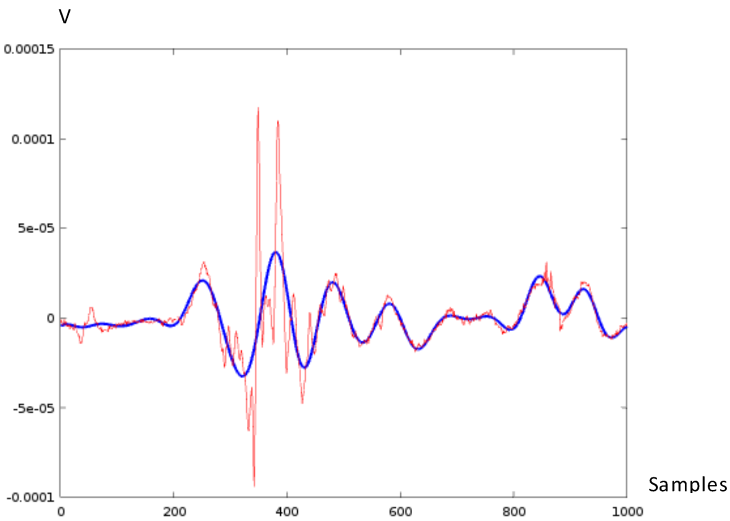


Figure 4.7: In red, correlated average for sensor 2. Load in left hand. In blue, the first band of the signal in red

In Figure 4.8 it is seen that both bands, the one of the arithmetic mean and the one of the correlated average, are very similar. The reason is that for low frequencies it is very complicated to observe cancellations when doing and average. These cancellations are produced when the signal changes very fast. For the first band the results of the mean and the correlated average are very similar.

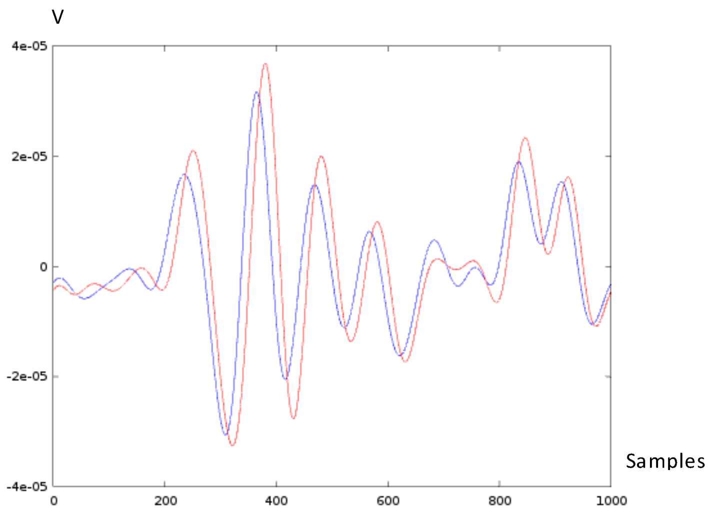


Figure 4.8: In red, first band signal of correlated average for sensor 2. Load in left hand. In blue, the first band signal of mean for sensor 2. Load in left hand

In the Figures from 4.9 to 4.12 it is shown in blue how are the signals corresponding to the second and third frequency bands. These bands represent the medium frequencies. Observe that the level of the signals is important. This means a big part of the content of the signal is located in these bands.

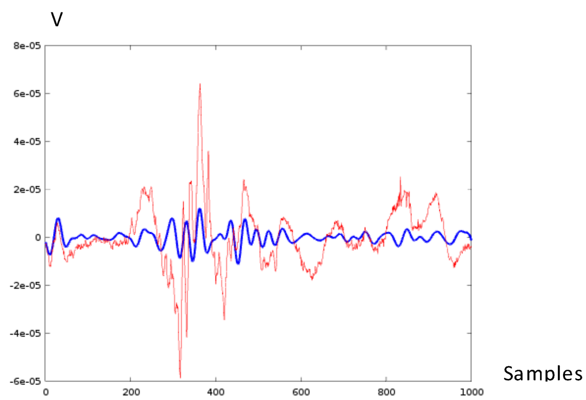


Figure 4.9: In red, arithmetic mean for sensor 2. Load in left hand. In blue, the second band of the signal in red

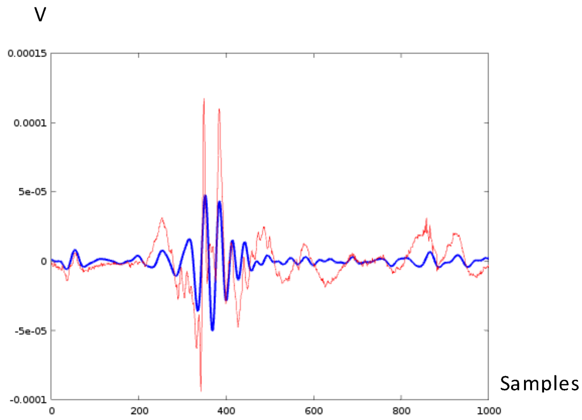


Figure 4.10: In red, correlated average for sensor 2. Load in left hand. In blue, the second band of the signal in red

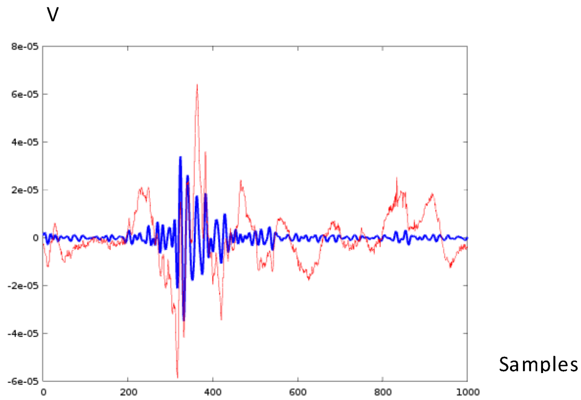


Figure 4.11: In red, arithmetic for sensor 2. Load in left hand. In blue, the third band of the signal in red

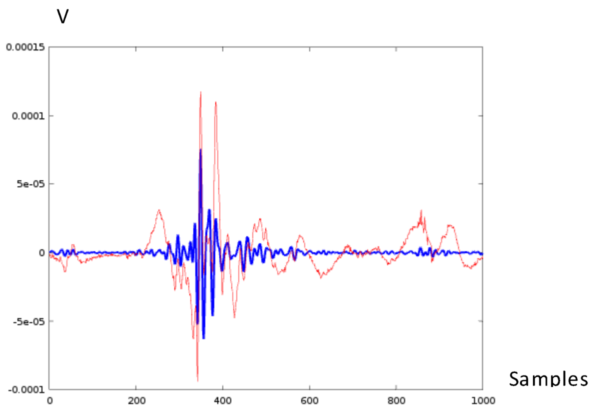


Figure 4.12: In red, correlated average for sensor 2. Load in left hand. In blue, the third band of the signal in red

In Figure 4.13 and Figure 4.14 it is shown that right now there is an evident difference between the mean and the correlated average. The effect of signals displacement now is visible. With higher frequencies, it is easier to have cancellations. With the correlated average these cancellations are avoided, so here is the improvement

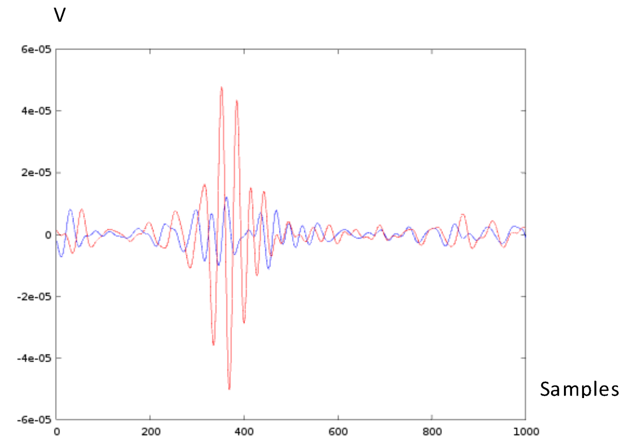


Figure 4.13: In red, second band signal of correlated average for sensor 2. Load in left hand. In blue, the second band signal of mean for sensor 2. Load in left hand

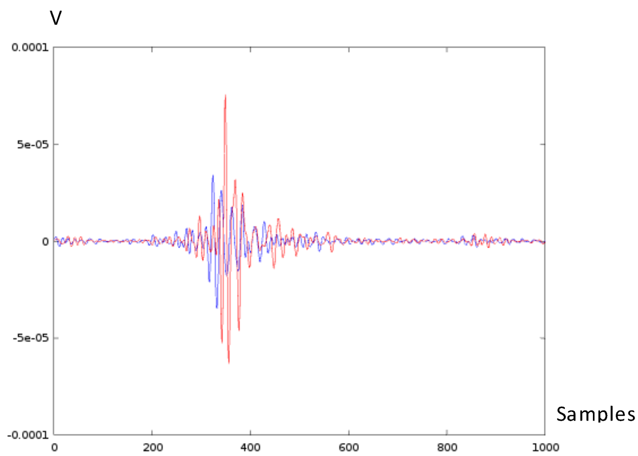


Figure 4.14: In red, third band signal of correlated average for sensor 2. Load in left hand. In blue, the third band signal of mean for sensor 2. Load in left hand

In the Figures 4.15 and 4.16 fourth band signals are shown. These bands represent the high frequencies. The level of the signal is very low for both of them. There is not a lot of information contained in this band.

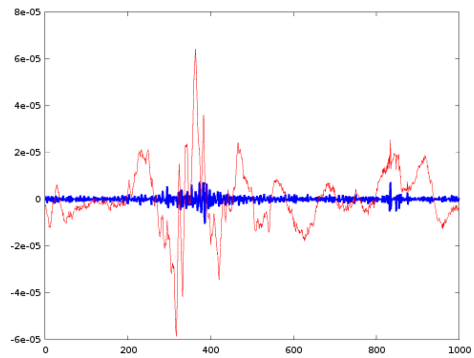


Figure 4.15: In red, arithmetic mean for sensor 2. Load in left hand. In blue, the fourth band of the signal in red

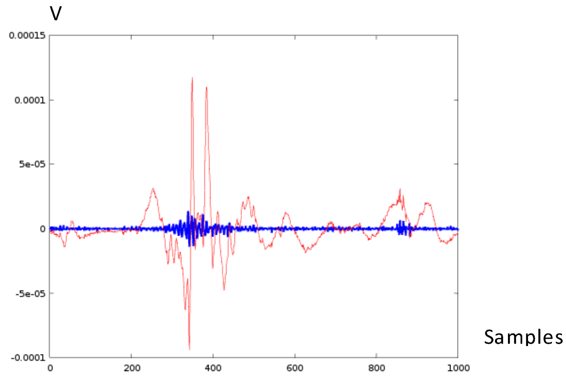


Figure 4.12: In red, correlated average for sensor 2. Load in left hand. In blue, the fourth band of the signal in red

In conclusion, it can be said that we can confirm by spectral analysis that the correlated average is better than the mean for obtaining the models.

For low frequencies the result is almost the same. However, for medium frequencies, where is located the important information of the signal, the correlated average has much better results. For high frequencies both of them are useless, but it is not a problem.

4.2.2 Sensors comparative

Talking about sensors comparative it is the same as talking about muscles comparative. As it has been explained during the thesis, the largest part of the information is contained in second and third bands. Let's use these bands then to compare the sensors

The aim is to compare the same muscle but in different legs. Let's see if there is some kind of relationship between the signals produced or not.

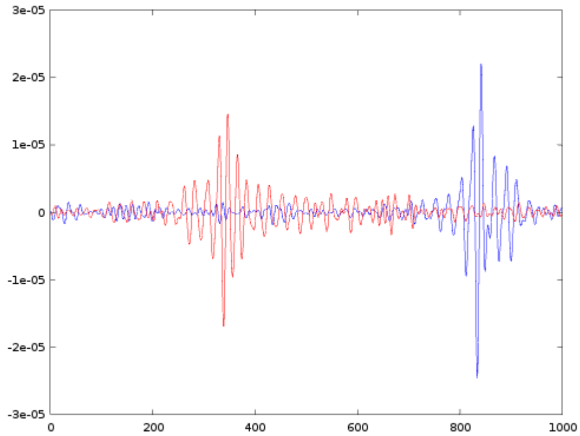


Figure 4.13: In red, third band of sensor 8. Load in both hands. In blue, the third band sensor 7. Load in both hands

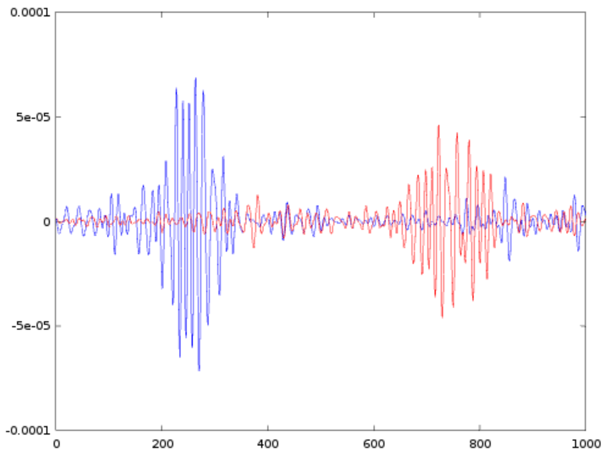


Figure 4.14: In red, third band of sensor 6. Load in the left hand. In blue, the third band of sensor 5. Load in the left hand

It is enough with the two examples of Figures 4.13 and 4.14 to notice that there is an evident relationship between muscles in the same position of a different leg. It is logic, when a muscle of one leg is being contracted the one of the other leg is being relaxed and the same when the opposite occurs. The difference between the excitation of one muscle and the other one is almost half a cycle, as it results logic.

Now let's take a look about which phase of the gait matches with the excitation of each muscle. The Figure shows in a very graphic way this topic. The sensors 1 and 3 were discarded because of problems with the data.

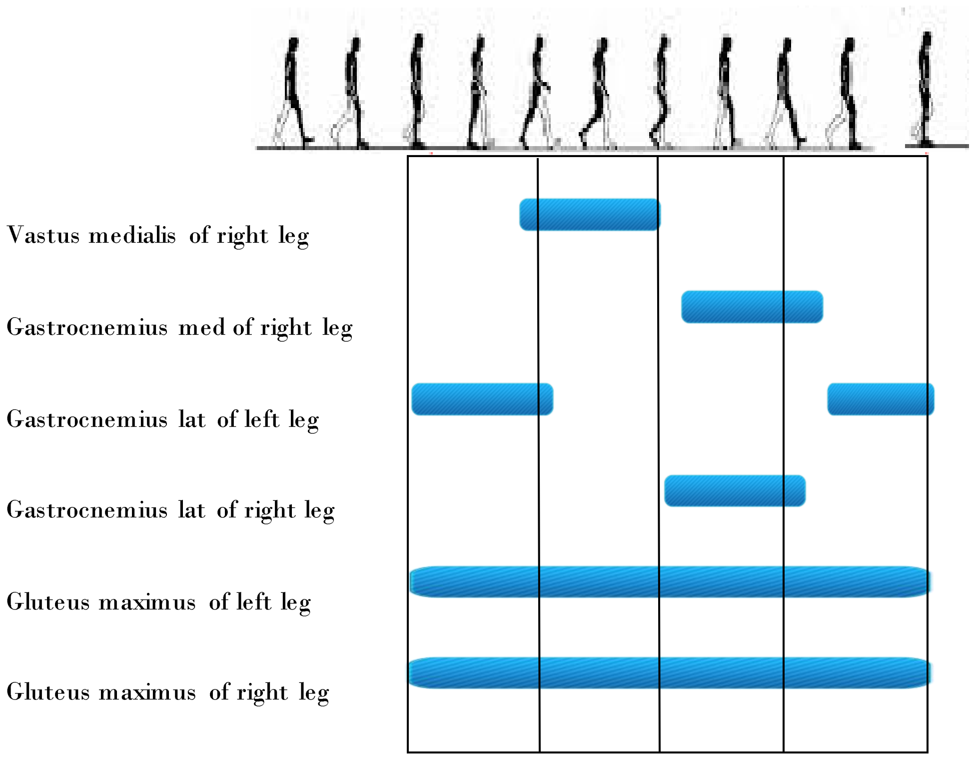


Figure 4.15: On/Off timing pattern of 6 muscles within a gait cycle. Blue bars indicate when the muscle is active

The activity of the gluteus is very particular and it is not easy to locate a special zone of the gait with more activity. It is logical observing the role of the gluteus during human gait. It is not the same as a muscle of a leg.

4.3 Final conclusions

Once the thesis is finished and explained it is time to reflect about the general and personal results after almost 5 months of dedication.

From a general point of view we can say that the goal has been reached satisfactorily. The original purpose of the thesis was to proportionate a database of objective models of EMG signals corresponding to human gait holding a 2 Kg load. This was the main goal at the beginning of the thesis and it has been reached. Unfortunately, some of the records of the experiment were in bad conditions and it was impossible to deal with them. For example, data from sensors 1 and 3 had to be discarded. Some cycles of other sensors had to be discarded too.

An important conclusion of this thesis is that the use of correlated average instead of classical arithmetic mean improves considerably the final models. As it has been shown, the medium frequencies are the most important in these signals, and in these signals the reliability of the correlated average has been proved.

Another aim for this thesis was to provide a guide for people who are starting to deal with EMG signals. I personally hope that this document could help someone someday. This thesis has been very interesting for me and I think that this subject (EMG) is going to be an important subject of study next years.

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