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Comparison of Posturographic Body-sway Measurements with Inertial Data of Parkinson Patients

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Informan:

Que el presente trabajo, titulado:

Comparison of Posturographic Body-sway Measurements with Inertial Data of Parkinson Patients.

Ha sido realizado y redactado por el mencionado alumno bajo nuestra dirección, y con esta fecha autorizamos a su presentación.

Granada, a 20 de julio de 2015 Fdo:

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Abstract

Posturographic Body-Sway Measurements are increasingly important in many fields of modern medicine, sport activities and teleassistance. Postural instability is an important contributor to incapacitation in elderly people and patients with neurological or motion disorders like people with Parkinson's disease.

This work describes the development of a comparative study between several systems to measure the Posturographic Body-sway and techniques and procedures to extract features of them. Along this document we describe, firstly, the most common instrumentation in these kind of experiments as well as the methods used for data analysis of Anticipatory Postural Adjustment (APA) in Parkison patients. Secondly, we will introduce a general description of all devices used to gather the necessary data for the development of this project. These devices are: the Gait Watch, a system based on inertial sensors for gait monitoring, a Force Platform, a system for force measurements and the Qualisys System, a system that uses speed digital cameras and markers attached to track motion.

The core of the project consists of comparing the signals obtained from the systems mentioned above. In the first place, we are going to compare the GW anf FP signals to determine whether we can obtain the same information of both systems and we can use the inertial sensors in place of force platforms. To do this, we will carry out the synchronisation of the signals, analysis of APA and the feature extraction of these signals. In this last aspect, we focus in PCA algorithm because it allows us the reduction of redundant information and the interpretation of multiple gait signals. In second place, we are going to analyse the Gait Watch system in comparison with the Qualisys Optical motion tracker. In this case, we will calculate the pitch angle for both systems. We will compare features like 'stride time' and angle. Before doing this, we explain the configuration of the Qualisys System and how we compute the angle for each point of time. In addition, we will do a feature extraction using both PCA and PLS algorithms and classification of data force in another different experiment with Parkinson patients and healthy people. This allows us to determine the accuracy of force data for the diagnosis of this disease.

Finally, we present a summary of the different fields of applications related to health-care and a brief business plan where we explain a description of a business idea and the most important aspects to take into account.

Abbrevations

APA: Anticipatory postural adjustments

SIPBA: Signal processing and Biomedical Applications

FP: force plate

GW: Gait Watch

QS: Qualysis System

PD: Parkinson's disease

IMU: Inertial Measurement Unit

MIMU: Magnetic Inertial Measurement Unit

EMG: Electromyography

MEMS: Microelectromechanical Systems

LTSD: Long Term Spectral Detector

FSD: Framed Spectrum Detector

COP: Center of Pressure

AP: Antero-posterior

ML: Medio Lateral

FIR: Finite Impulse Response.

PLS: Partial least squares.

PCA: Principal Components Analysis.

ROC: Receiver Operating Characteristic.

AUC: Area Under Curve.

TPR: True-Positive Rate.

FPR: False-Positive Rate.

SVM: Vector Machine Classifier

Contents

List of figures

List of tables

Chapter 1

Introduction

1.1 Context

Parkinson's disease is a chronic and progressive movement disorder caused by the malfunction and death of neurons in the brain. Some of these neurons produce dopamine, a chemical that sends messages to the part of the brain that controls movement and coordination. Thus, as Parkinson's disease progresses, the amount of dopamine produced in the brain decreases, leaving the person unable to control movement normally [5].

The disease must be diagnosed by an experienced neurologist. There are no tests that clearly identify the disease, but brain scans and blood test are sometimes used to rule out disorders that could give similar symptoms. One of the main concerns of people with PD is the fear of falling. First motor symptoms in this disease, like rigidity (stiffness of the limbs and trunk), bradykinesia (slowness of movement) and postural changes, contribute to risk of falling. Difficulties in the adaptation of neck and trunk cause postural instability, which, in turn, increase the possibility of suffering a fall.

The center of body mass of a person is situated below the navel and the legs and works as a support base. In PD it is common that the center of mass goes out of the support base. This fact causes losses of equilibrium in activities such as getting up, bending, spinning around quickly or walking. Also, falls can occur due to a damage in postural reflexes (a series of complex movements that we carry out in an automatic way in order to maintain the equilibrium when we get up and walk), postural changes (tendency to lean forward using short, quick steps and reduced arm movement) and freezing (inability to step that delays gait initiation or interrupts ongoing gait). Research in this field is of vital importance to contribute to the improvement of advancement of knowledge about the disease. Scientific research can be the base for field applications that help to improve the people life with PD[6][5].

With this Project, we aim to continue the research line initiated by Dr. Alberto Olivares, member of the SIPBA (Signal Processing and Biomedical Applications) research group of the Department of Signal Theory, Telematics and Communications of the University of Granada, Spain, and Prof. Dr. Med. Kai Bötzel, head of the Motion Analysis and Deep Brain Stimulation Laboratory of the Department of Neurology of the Klinikum Grosshadern based in Munich, Germany. In his Ph.D. dissertation, Dr. Olivares explains [7] different signal processing techniques to analyze information from inertial sensors to monitor human body motion. Specifically, our work will be focused on signal processing of data gathered by a force plate and a wearable motion analysis system based on inertial sensors, feature extraction and classification. Nevertheless, this master thesis is part of a broader project which has many different layers (instrumentation, data gathering, firmware, signal processing) in which other people have been working during the last 5 years.

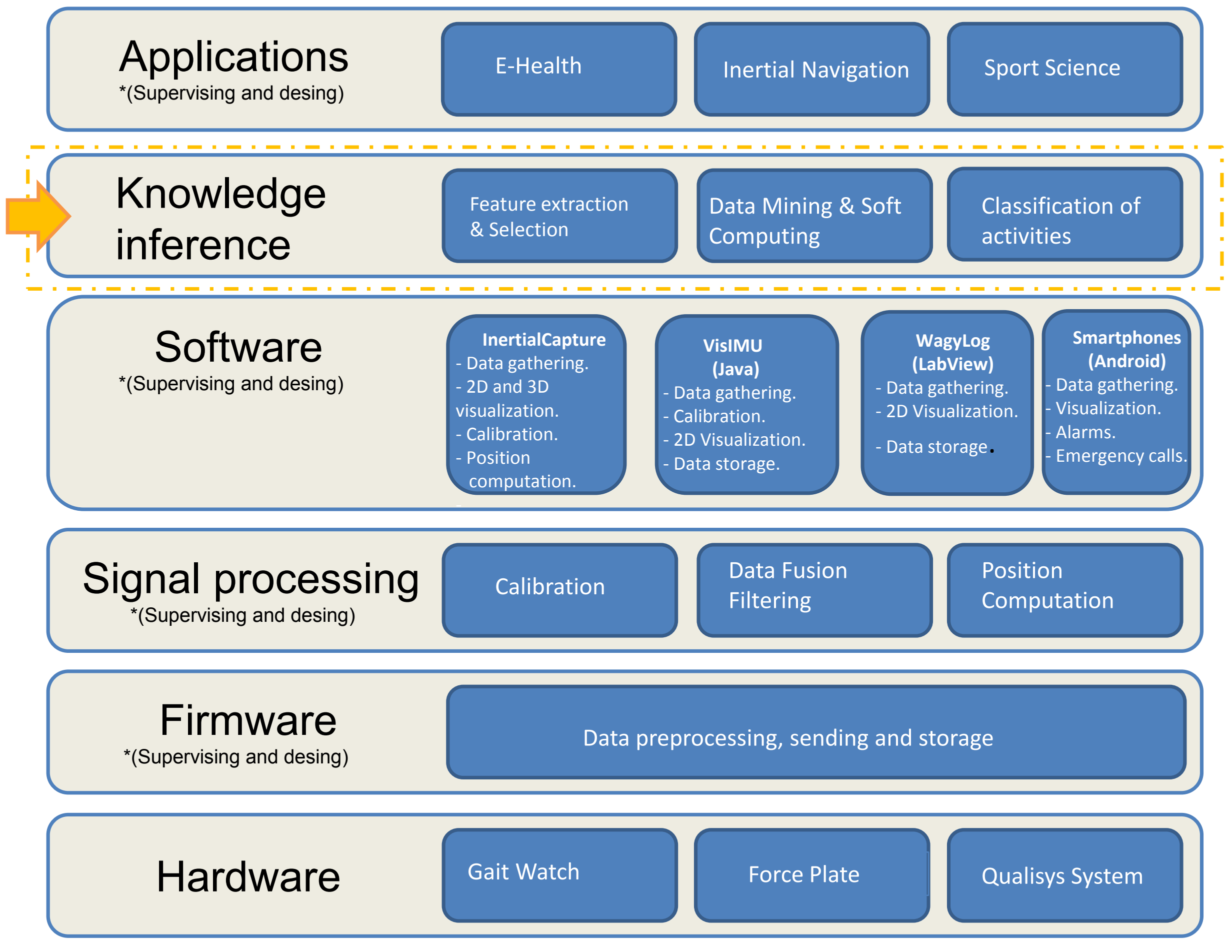

Figure 1.1: Layer structure of this project. Knowledge inference is highlighted as it includes the core of our work.

1.2 Motivation

Parkinson's disease is the second most common neurodegenerative disorder, it is extended globally and affects as much to men as to women. PD is more common among the population over 60 years old. It is estimated that seven to ten million people worldwide are living with Parkinson's disease. To this date, there is no cure to PD, so all efforts are focused on improving or prolonging the functionality of the patient for as long as possible. Therefore, it is an incentive to work in this field[6][5].

Furthermore, Intel and Michael J.Fox Foundation have recently teamed up to create a sensor technology and analytics platforms for Parkinson's treatment and monitoring. Fox Foundation CEO Todd Sherer told Fast Company *'Parkinson's is a motor disorder for the most part, with slowness of movement, tremors, falls, problems sleeping, and many disease symptoms. The way it is measured right now requires episodic periodic visits to a neurologist, who puts patients through fairly subjective and coarse clinical tests, there are many 1-2-3-4 scales. What we need to advance is research that is a much more consistent and objective measure of the disease. People live with Parkinson's 24 hours a day, 7 days a week, not just when they're in the doctor's office'*[1].

The goal is to track the symptoms and progress of Parkinson's disease day by day, and using this information to research the disease in depth.

Figure 1.2: Illustration of sensors distribution thought up by Intel and Mjf[1].

Diane Bryant, senior vice president of Intel's Data Center Group, said in a release [1] *'Emerging technologies can not only create a new paradigm for measurement of Parkinson's, but as more data is made available to the medical community, it may also point to currently unidentified features of the disease that could lead to new areas of research'.*

1.3 Goals

The main goal of this project is to perform a thorough analysis of Anticipatory Postural Adjustments (referred to as APA in the remainder of this document) of PD patients. APAs can be used to characterize step initiation deficits in subjects with PD and also as a differentiating factor which may help early diagnosis of the disease.

To this purpose, we will make use of a database gathered by the medical team in Munich. The database contains both data from a force plate and inertial sensors. The patients wear the motion monitoring system containing the inertial sensors while they step on and down the force plate.

Once the measurements are made, the main objective is to determine whether it is possible to use inertial sensors to extract the information provided by the force plate. That is, we will evaluate the correlation between inertial sensor measurements and the force plate measurements in order to study the feasibility of the wearable device to study APAs in an ambulatory way.

Furthermore, we will conclude determining whether it is possible to classify data force between Parkinson patients and control subjects for the diagnostic of this disease.

Additionally, we will try making a comparative study between the pitch angles calculated in both inertial sensors and Qualisys optical motion tracking system. The precision of this system allows its use as a reference system to evaluate portable motion tracking systems such as the GaitWatch. To carry out this comparison, healthy people walked over a treadmill at different velocities.

In a nutshell, the ultimate goal is to determine whether doctors can substitute force plates (which strongly limit the range of action of the patients) by the inertial wearable system (which allows ambulatory analysis).

1.4 Project structure

This document presents a slight variation from the standard structure in which there is a chapter including all the theoretical basis, followed by another chapter including all the experiments, results and their discussion and a final chapter drawing the conclusions. Instead, every separate chapter has its own introduction, theoretical fundamentals, experiments, results, discussion of results and some brief conclusions. This structure makes every chapter self-contained and, therefore, they can be read separately.

Therefore the document is divided as follows; chapter 1 presents a brief introduction to the project. This includes context, motivation, goals and the state of the art; chapter 2 deals with Hardware description used for the development of the project. In this chapter it is explained the basis of Gait Watch, the Force platform and the Qualisys System.; chapter 3 includes the protocol followed by the patient to do the experiments while the data were being gathered by the GaitWatch System and the Force Plate. Then, we explain the procedure to carry out the synchronisation between the signals of both systems. After this, we extract the interesting features of these signals to characterise the Anticipatory Postural Adjustments in Pakinson patients. In this section, one of the most interesting method used is the PCA algorithm to extract the relevant information of the data. At the end of this chapter we explain the results and some conclusion obtained from them; chapter 4 includes a new experiment with force sensors underneath feet. The data gathered with them are processed for feature extraction with PCA and PLS algorithms. Also it is carried out a classification between Parkinson patients and control subjects; chapter 5 talks about the comparison between the Gait Watch and the Qualisys system. This chapter includes, the same as in the previous case, a brief introduction, theoretical fundamentals to calculate the pitch angle in the Qualisys system, the feature extraction and the explanation of the results; chapter 6 shows some interesting applications in the healthcare field like diseases and daily activities. Also, we propose a business idea thought during the development of the project as well as a canvas model that summarises the business plan; finally, chapter 7 includes the general conclusions and summarizes the most relevant parts of everything that is presented in the rest of the chapters. We also discuss about future research lines and how we will orient forthcoming work.

You can see a visual summary of the project structure in the first appendix.

1.5 State of the art

We will start by studying some of the current devices used for body motion monitoring as well as their benefits.

Later we will search the methods and experimental procedures used in several studies to analyse of Anticipatory Postural Adjustments in different cases, as well as their applications.

Finally, we will speak about the most common calibration techniques, signal processing and classification.

1.5.1 Instrumentation

There are several device types used to measure APAs. The most important are: electromyographs, force platforms, inertial sensors and devices based on cameras.

Electromyography (EMG) is a technique that gives us information about the electrical activity produced by skeletal muscles (See figure 1.3). The electromyograph can detect the electrical activity due to a electrical potential difference generated by muscle cells. It is very useful to analyse posture and to locate injuries like muscle paralysis [8] [9].

So far, most of studies have included like measurement devices, among other things, a platform sensitive to force and pressure. However, the cost and complexity of APAs measurement with a traditional movement analysis, using force platform and EMG System limit their applications in the clinical practice. Therefore, small inertial sensors are used recently because they are cheaper and more portable. But even so, we have used this platform, considering the possibility to solely use inertial sensors in the future [10] [11].

Devices based in commonly used inertial sensors are IMU (inertial measurement unit). IMUs are a electronic device that measures and reports about speed, orientation and gravity force of equipment, using a combination of accelerometers and gyroscopes. In addition, these sensors can be combined with magnetometers to form a MIMU. Some current MIMUs are: 3DN-GX4-45 [12], xsens-mvn [13] and mvn-biomech [14], all of them use Microelectromechanical Systems (MEMS).

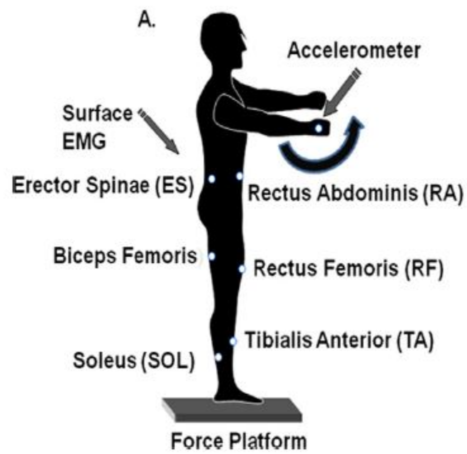

Figure 1.3: EMG, accelerometers y platform [2].

There are infrared-reflective markers that give us a complex posture measurement. They are attached to the body and can provide information about postural strategies, so we can know if the subject uses the ankle strategy or the hip strategy. For example, figure 1.4 shows the System.

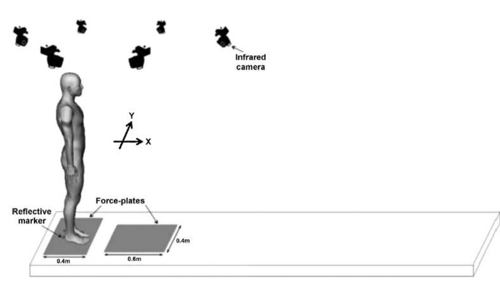

Figure 1.4: Illustration of the experiment with infrared-reflective markers[3].

As mentioned previously, it is possible to use sensors based on cameras that generally are part of an optical System of movement capture such as Kinect. [15].

1.5.2 Methods and procedure

So far, a lot of studies about Anticipatory Postural Adjustments are been done, mainly in the last six years. The finality of most of this research is to be able to deepen knowledge about the posture prior to step initiation, and whether there are postural patterns and conditions on which they depend.

If we analyse the state of the art of APAs, we can find that first investigations tried to verify whether APAs are associated to conscious movements or not, this hypothesis was confirmed and the conclusion was that it is more probable that the adjustments do not appear if step initiation is not planned. It is essential for balance control in gait initiation because we can use this knowledge to prevent the falls in some people with movement difficulties[16][17][3][18][19].

After this, researchers tried to explain the influence of other variables, such as several exercises that stimulate different muscles and the reaction of others[2]; the age influence for generating postural patterns [20] [21]; the signal type that initiates the movement (visual or auditory) due that it affect initial posture [16][22][23][24]; the fear to fall because it can do that patients adopt different postures[25]; neurodegenerative diseases like Parkinson and Multiple Sclerosis[10][26][25][27], or cerebral palsy, like hemiplegia and diplegia, [27], generate differences in the APAs too.

All these studies are very important in medical applications. For example, as mentioned previously, there are diseases that affect the Central Nervous System, so it affects the mobility too. Then, it causes falls in many occasions, therefore people that suffer the fall have fear of falling again. The fact that fear of falling causes variations in the APAs making people fall again can help us to prevent this fact.

1.5.3 Data Analysis

In the last years, a lot of works about calibration of accelerometers and gyroscopes have been carried out, although most of them show little variation with others studies done before. One of the most important research works [28] explains one form to do the calibration putting the accelerometers in six different positions and applying simple algebraic algorithms to the obtained data. The gyroscope is calibrated in a different way, using a process based in a known rotation.

There are other methods that try to be more precise, increasing the number of positions where data are recorded [29]. Also, there are others type of calibration techniques like algorithms based in basic algebraic calculation or in FIR filters [7].

As for estimation of orientation for human-body monitoring, if we study the works done so far, we can see that almost all use a Kalman Filter. However, the accuracy of Kalman filters can be poor if motion being monitored is intense [7].

Finally, we will analyse the state of the art of movement recognition in humans, feature extraction and classifiers. Quickly, we can see a lot of information about classification because there are a lot of articles and books about this. However, there are others type of studies, that we will consider [30] [31][32], that explain methods for obtaining gait features, pattern definition and human activity recognition based on a sensor weighting hierarchical classifier and others algorithms such as PCA and PLS [33] [34].

Chapter 2

Hardware Description

Along this chapter we will introduce a general description of all devices used to gather data for the development of this project.

It should be noted at this point that there are two clearly differentiated parts. In the first one, we work with Force Plate and GaitWatch data, taking out their characteristic signals and synchronising them. In the second one, we work jointly with Gait Watch and Qualisys System data for the purpose of comparing the accuracy in the calculated orientation angles.

2.1 GaitWatch

GaitWatch is an Inertial Measurement Unit (IMU) designed for gait monitoring of patients. It was developed by Prof. Dr. Med. Kai Bötzel at the Department of Neurology of Ludwig-Maximilians University in Munich in conjunction with Dr. Alberto Olivares Vicente from the Department of Signal Theory, Telematics and Communications of the University of Granada. [4].

The system is composed of the central processing unit and a set of measuring units which are wired to it. The measuring units are placed in the patients' thighs, shanks, arms and trunk.

The central processing unit has a microcontroller which is in charge of gathering the data from the external measurement units and writing them to the memory card. So, this central unit is placed on the trunk inside a box and it contains an AL-XAVRB board with an AVRATxmega processor which contains the necessary embedded firmware to gather the data from all the measurement units and store them in a microSD card. Also, the trunk box contains some embedded magnetic and inertial sensors.

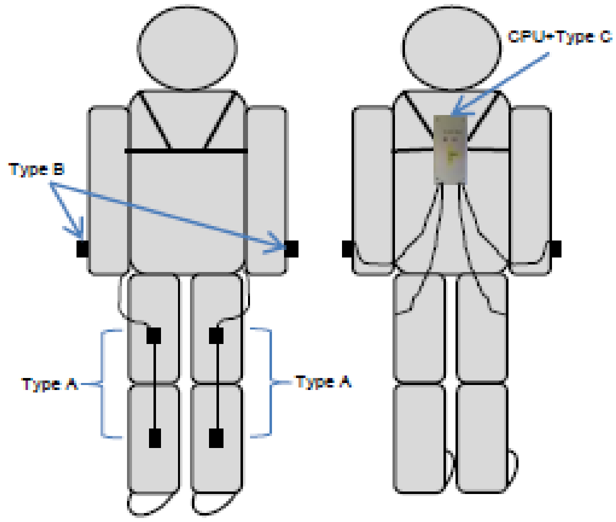

Figure 2.1: General Diagram of the Gait Watch.

Figure 2.2: Devices used in Gait Watch System.

There are three different kinds of external units with the following components:

- Type A (thighs and shanks):
  - ◇ IMU 5 from Sparkfun. IMU 5 contains an IDG500 biaxial gyroscope (from which only Y axis is actually used) with a measurement range of $\pm 500 deg/s$ and a $\pm 3g$ triaxial accelerometer, ADXL335 .

- Type B (arms):
  - ◇ IDG500 biaxial $\pm 500 deg/s$ gyroscope.
- Type C (trunk box):
  - ◇ ADXL345 triaxial accelerometer with programmable range ($\pm 16g/\pm 8g/\pm 4g/\pm 2g$).
  - ◇ IMU3000 triaxial gyroscope with programmable range ($\pm 250/\pm 500/\pm 1000/\pm 3000(deg/s)$).
  - ◇ Micromag3 triaxial magnetometer ($\pm 11 Gauss$).

2.2 Force Platform

Force Plate (FDM-S Multifunction Force-measuring Plate, Zebris) is a System for force measurement and it can be used as a complete measuring unit for stance and roll-off analysis [35].

This platform consist of a large number of force sensors and enables the distribution of static and dynamic forces under the feet to be analyzed during stance and gait (65x40 cells of sensors). As a result, foot deformities, foot function and posture can be analysed and are available as an evaluation report [35].

Therefore, this gathered information can be used afterwards to analyse the postural adjustments with the right software.

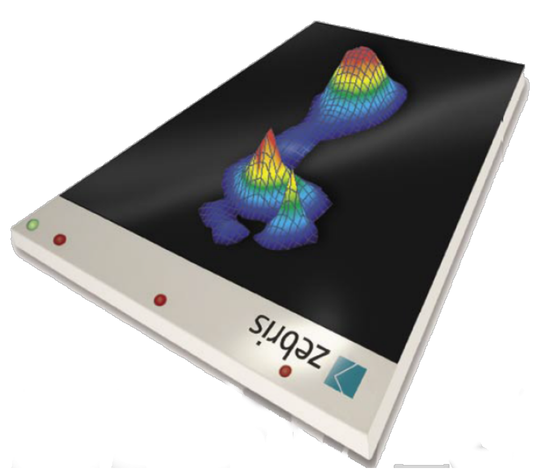

Figure 2.3: Platform used to analyse the force under the feet.

2.3 Qualisys System

The Qualisys optical motion tracker is a system that uses high speed digital cameras to capture the motion of a measurement object with passive or active markers attached [4].

This technology is used by researchers and clinicians to understand the basics of human motion or improve treatment during a rehabilitation process. Also, it used in industrial applications, for example, interior design of a car can be improved by using this System to evaluate the comfort and safety factors for the car driver [36].

The technology is precise and delivers high quality data to the observer in real-time. The core component of the Qualisys System is one or more infrared optical cameras that emit a beam of infrared light. Also, there are small retro-reflective markers on a object or person. When the cameras emit infrared light onto the markers, these reflect the light back to the camera sensor and this information is used to calculate the position with high spatial resolution [36]. The used system has eight cameras which are distributed around a room.

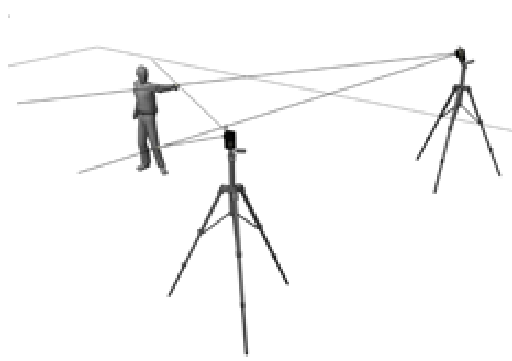

Figure 2.4: Qualisys optical motion tracker.

The provided software tools allows to perform basic motion calculations, such as speed, acceleration, rotation and angle, as well as other more complex calculations. The precision of this system allows its use as a reference system to evaluate portable motion tracking systems such as the GaitWatch [4].

Chapter 3

Gait Watch and Force Plate signals processing

3.1 Introduction and chapter's structure

Along this chapter we will introduce the protocol used to obtain the Gait Watch and Force Plate signals as well as the developed software to synchronise and analyse the signals that characterise the anticipatory postural adjustments before gait.

On the one hand, we will carry out the synchronisation between the signal from inertial sensors (Gait Watch) and the force signals from the platform. It is very important for comparing both devices, determining the differences and similarities and finally resolving if we can obtain the same information from both systems.

On the other hand, we will analyse the most interesting signals to characterise the APAs, obtaining the parameters of them which may be of interest.

3.2 Data gathering Protocol

Prior to start of data gathering, it is necessary to set up the protocol of the procedure that patients have to carry out while the data are recorded. The establishing of this procedure is very important so that the synchronisation works properly because we have to identify a clear movement in both signals to match one signal with the other at the same time. In addition, the realised movements must be representative to obtain conclusive data which help us to extract characteristics for the purpose of identifying differences between patients and control subjects subsequently.

The steps followed by the patients are detailed hereafter:

1. Subject stands in front of the Force Plate.

2. Gait watch record starts for data gathering.

3. Force plate record starts for data gathering.

4. Subject makes a step onto the platform.

5. Subject stands on the platform a variable time between 2 and 10 seconds.

6. Subject makes some step forward and turns left to stand in front of the platform again.

This procedure is repeated ten times by each subject in order to characterise better the movement made. It is important to clarify that the GaitWatch recordings contains all these ten episodes in a single file and the platform recording only contains one episode in each file. So, this is a fact that we have to consider to do the synchronisation.

3.3 Synchronisation

3.3.1 Introduction and chapter's structure

One of the most important aspects whether you have data acquired from multiples devices or channels is the synchronisation. If these data are not appropriately correlated or synchronised, the analysis and conclusions will be erroneous. Also, it is very important to automatize the process when you have data on a broad scale. Therefore, the following sections explain how the information has been obtained and processed automatically, as well as what features have been calculated to characterise the movements of the patients and to carry out the synchronisation between the Force Plate signals and GaitWatch signals. This content is superficially depicted in 3.1.

3.3.2 Design of developed code in Matlab

3.3.2.1 Selection, reading and obtaining of information from the excel file

All patients data, that is, the different files that have been generated after the gathering (of the force plate as well as Gait Watch), date, duration of the experiment and other observations are saved in a Excel file.

In order to automate all as much as possible, we developed a script which is in charge of extraction of the necessary data (files names) to carry out the appropriate calculations for each patient.

At the end of this fraction of code, we save all file names of both systems (force plate and Gait Watch) corresponding to each patient, in order to access and extract them posteriorly.

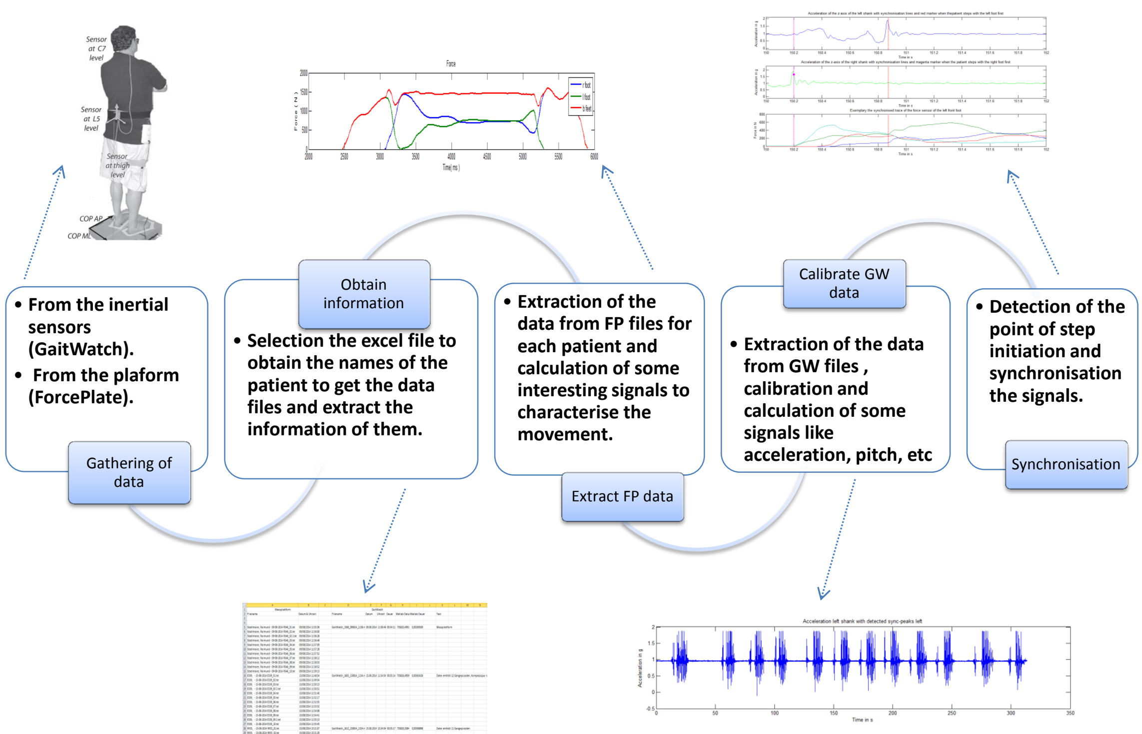

Figure 3.1: Diagram of the Synchronisation's progress.

3.3.2.2 Extraction of the forceplate data

As we said before, the force plate data files are recorded independently, that is, there is a *.txt file for each repetition of the experiment. Each file contains the force data of the toes and heels of both feet. It actually carries out a distribution of the sensors to cover these four segments3.2. Every measure is obtained for each point of time according to the sample frequency. Also, this file contains the force data from each cell that is part of platform in each frame3.3.

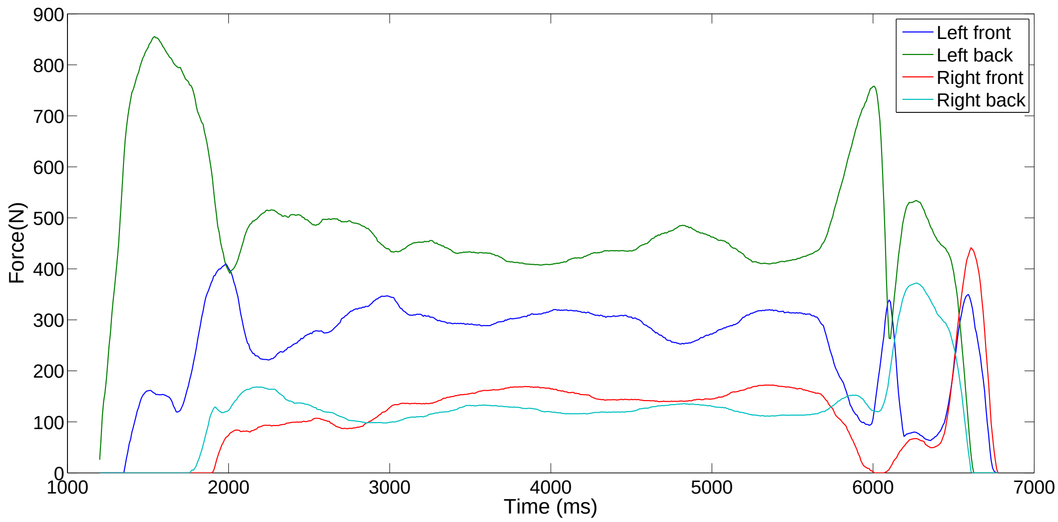

Figure 3.2: Force in each body segment.

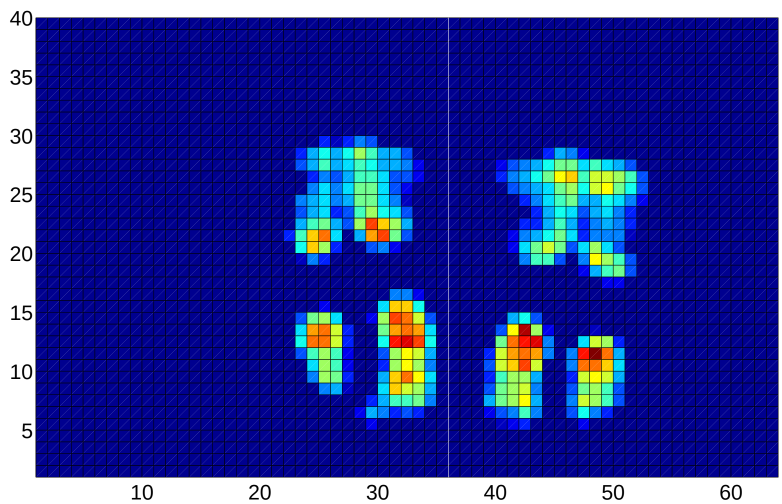

Figure 3.3: Pseudocolor with the force in each cell of the platform.

Once we recover these data, some parameters are calculated for the movement characterization carried out over the platform.

- **Midline**: it represents the midline between both feet. This is important to find the gap between feet and it gives us an idea of their position in the platform. Thus, we carry out the sum of cells force in the anterior-posterior direction. So, this line is in the minimum between two maximum corresponding to the position of both feet. We use this parameter to calculate the center of pressure.

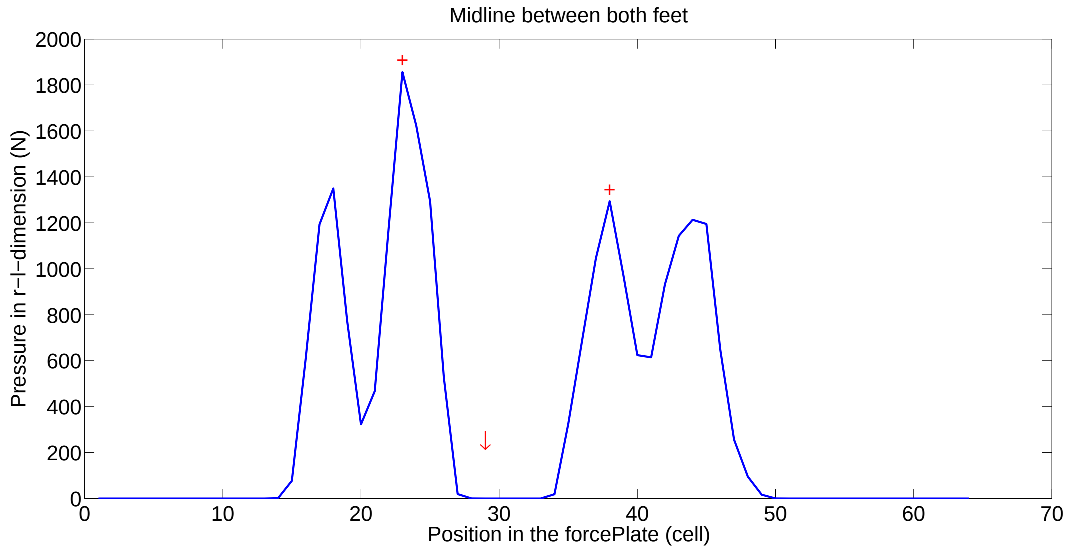

Figure 3.4: Midline between both feet in platform.

- **The total force in the platform for each point of time**: This signal is useful to do the synchronisation since we can determine clearer when the patient touches the plate.

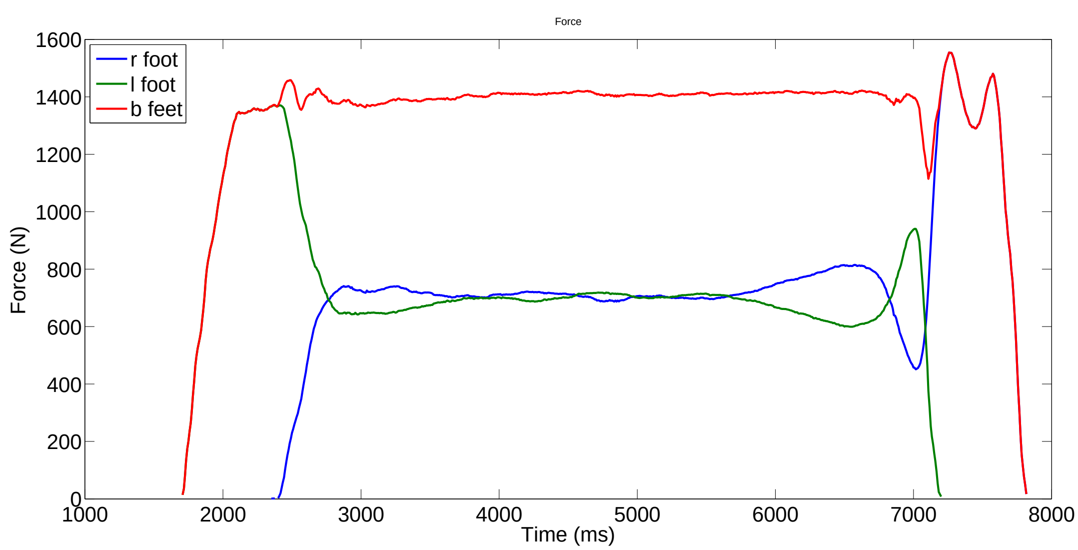

Figure 3.5: Total force in the platform of the right, left and both feet.

- **Antero-posterior COP**: Center of Pressure in forward-backward direction.

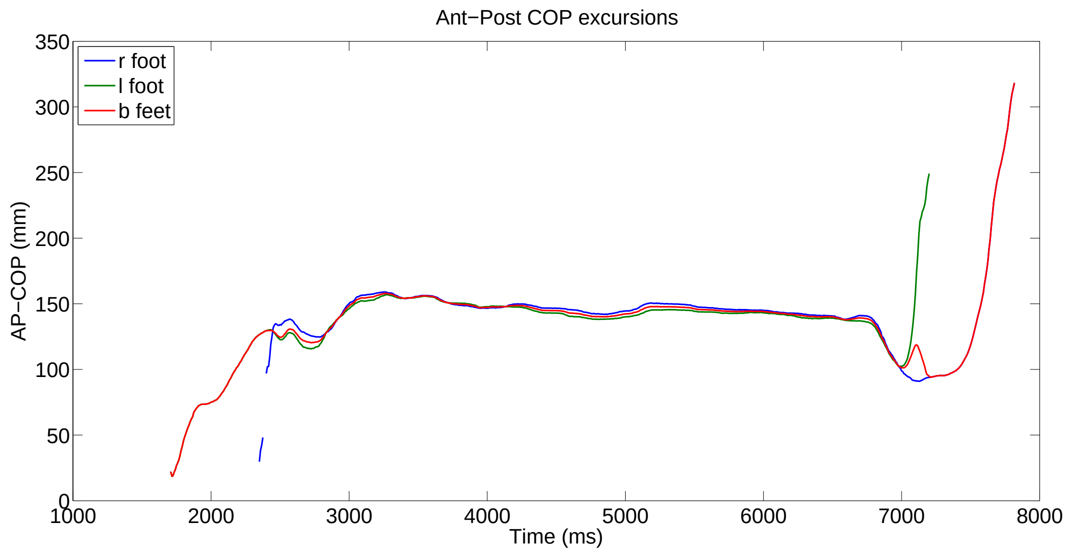

Figure 3.6: Center of Pressure in Antero-Posterior direction.

- **Medio-lateral COP**: Center of Pressure in right and left direction.

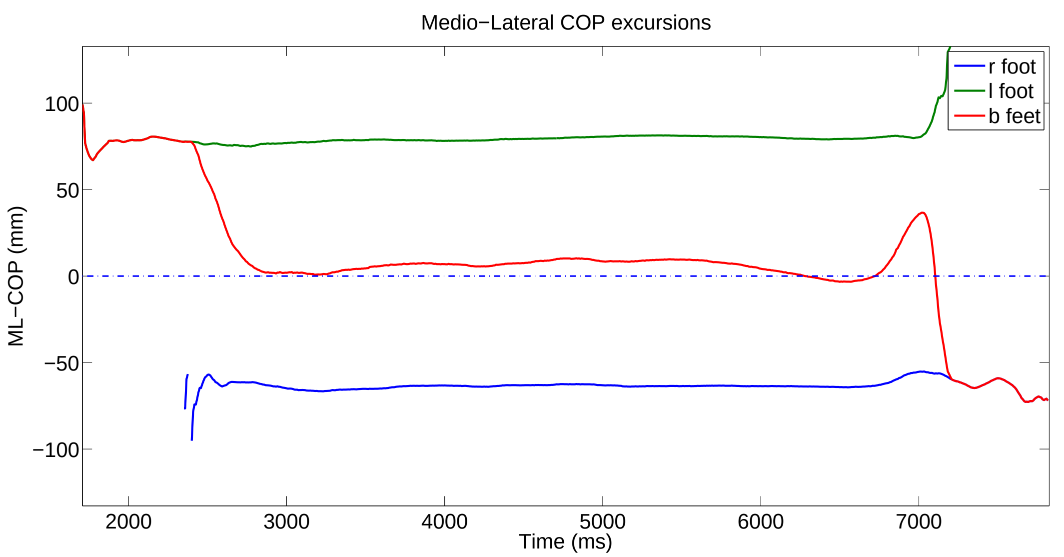

Figure 3.7: Center of Pressure in Medio-Lateral direction.

Center of Pressure can be expressed as follows:

$$R = \sum_{i}^{n} m_i r_i \tag{3.1}$$

Where R is the *"Center of pressure"*, M is the total force and mi are the force that are located in space with coordinated ri, in this case, in the plane. This location (ri) is calculated with respect to the midline.

These signals help us to characterise Anticipatory Postural Adjustments before gait. APAs indicate the movement or swinging of body before walking or carrying out some movement. Thus, these are the interesting measures to compare between each repetition as well as each patient to characterise the movement, determine if there is a pattern and figure out the differences and similarities between them.

All these signals are saved for each cycle in a single variable corresponding to the patient.

3.3.2.3 Calibration of the GaitWatch data

When we are working with sensors, calibration is one of the most important aspect that needs to be carried out. Prior to the calibration process, the information at the sensors will be a signal composed of integer numbers or real numbers bounded into a range which is determined by the precision of the sensors and converters. These numeric values lack of physical value, so it is absolutely necessary to convert them into a scale that can be measured in physical units.

The sensors present several errors due to some effects like scale factors may not be linear or the triad is not perfectly orthogonal. To remove these undesired effects, the software include a model to compensate this before the calibration. To do so, we have used the code made by Dr. Alberto Olivares Vicente in his doctoral thesis[7], with minor modifications of his work.

Besides the unwanted effects mentioned above, the output of magnetometers is distorted by wide band measurement noise appearing several large peaks of noise in the signals. To remove this automatically, we used a threshold considering that these peaks are much greater than the mean of the signal 3.8.

The erroneous values in the magnetometer signal are removed substituting these samples by the subsequent value unless the erroneous value is in the last position of the signal, in which case it is substituted by the preceding value.

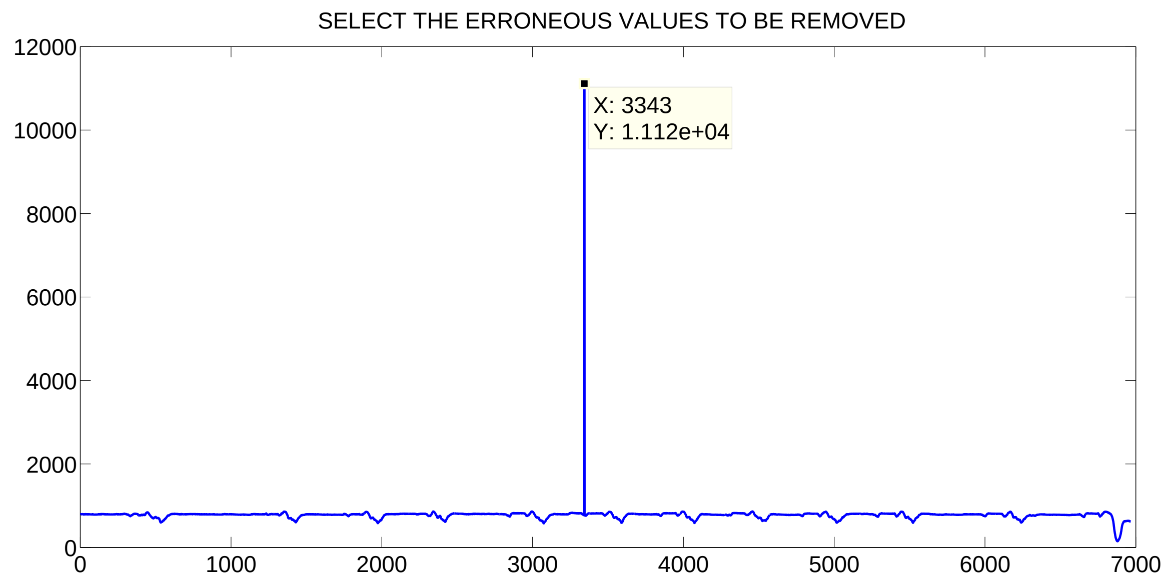

Figure 3.8: Value erroneous in magnetometer signal detected automatically.

3.3.2.4 Synchronisation

In this section we will explain how we carried the synchronisation of the Force Plate and GaitWatch signals and the considerations adopted to do it properly.

The first step is to detect when the step happens in both systems. In order to do this, we will use the completed force from Force Plate system and shank acceleration from the Gait Watch accelerometer. We chose these signals because it is easy to see in them the point when the patients step.

Once we have selected the right signals to do the synchronisation we have to differentiate each cycles in the acceleration signal because we have all repetitions together in the same file. To do this, we used the activity detection code implemented by Dr. Alberto Olivares Vicente in his Doctoral thesis. Figure 3.9 shows the result.

In addition we did a comparative study testing two different methods based on the computation of the spectrum (Fourier Transform) of the input signal. Also, we tried several input signals to determine which is the best option to do the motion detection in this case.

We will use the Long Term Spectral Detector (LTSD) [37] and a variation of this called Framed Spectrum Detector (FSD). Spectrum-based methods have been used in others kinds of applications like Voice Activity detection [38][39] and activity sequences detection such as running or sitting-standing up[7] .

The technical difference between LTSD and FSD is that the first one computes the Long term spectral Envelope whereas FSD uses the spectrum of each frame in which the input signal is divided[7]. What we observe when we use them in our signals is that the results are better when we use LTSD instead of FSD method in most of the cases3.9.

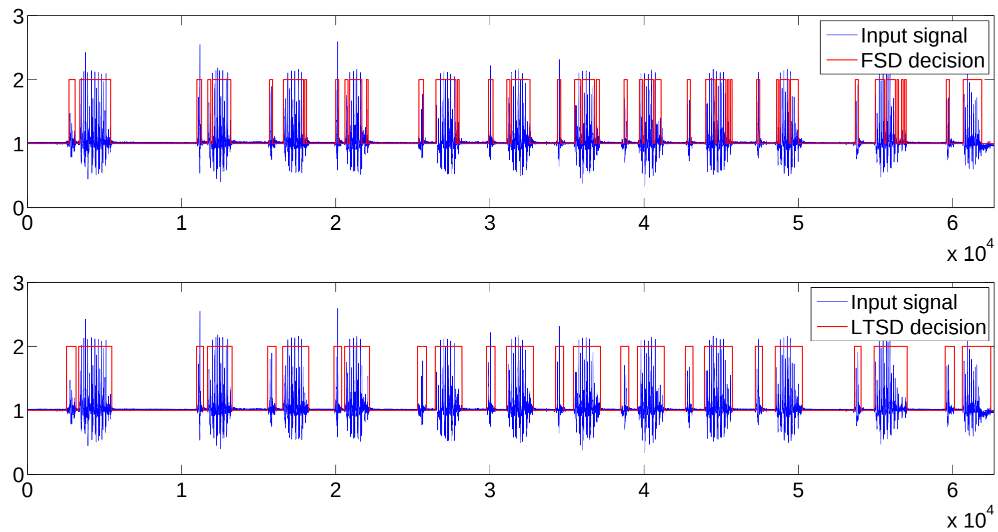

Figure 3.9: Activity Detection with FSD and LTSD Algorithm.

The LTSD method has a better decision rate than the FSD method because it is designed to work under conditions where the SNR is low, i.e the signal present large noise[7]. In our case, we want to detect the different cycles that correspond to each repetition so the different peaks of activity inside each period can be a problem to do the detection because they can be interpreted as noise by the detector. Thus, the LTSD method is more interesting for this type of signal.

Once we select the best method for detection we tested several input signals for the detector: shank acceleration signal, absolute value of the shank acceleration signal and module of the shank acceleration signal. Finally, the best result was obtained when we used the module of the shank acceleration signal because when this input signal is used in the resulting output signal it is easier to distinguish the different episodes.

Furthermore, the motion activity detection was carried out for the right leg as well as for the left one. It is not necessary in some cases when the patient does the movements or activities quickly since the detected activity interval includes both movements in the same episode. However, when patient waits some time to step again in the same repetition, it is possible that some step is not include in the interval thus the result would be erroneous. Therefore, to implement a general robust we need to differentiate between both feet.

Once the cycles have been separated, we are going to detect the key points in the signals to do the synchronisation.

On the one hand, the time point when the patient does the step in the platform is exactly when the person touches it, that is, the time point that corresponds to the first sample in the force signal with a value other than zero.

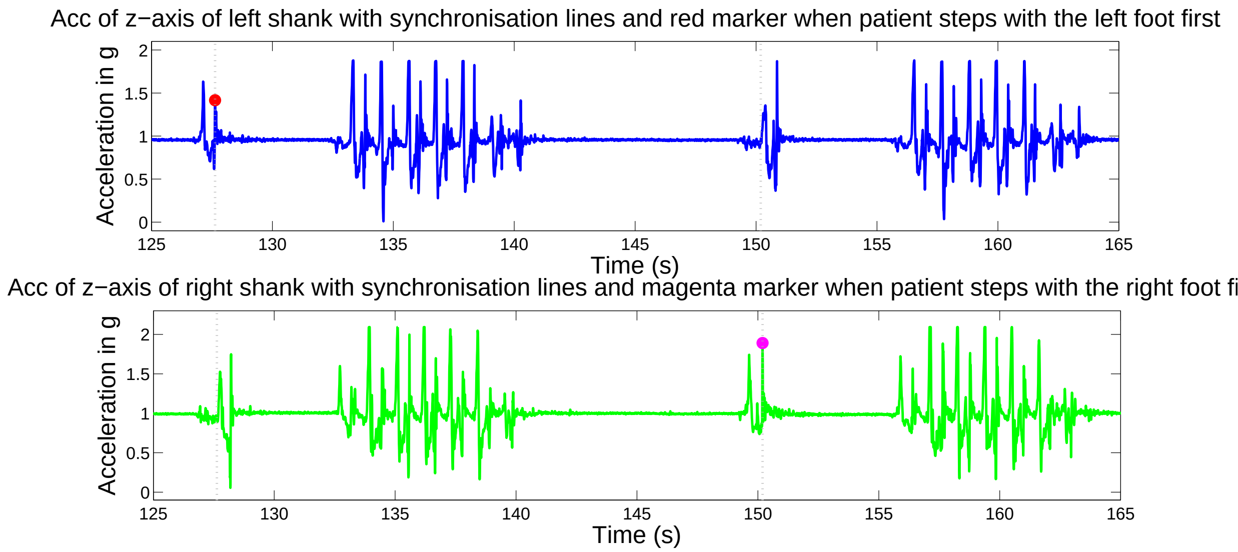

Figure 3.10: Accelerometer signals when the patient starts to step with the left and right foot respectively.

On the other hand, in the acceleration signal case, this fact happens in the second positive peak3.11. The reason is that when patient does a step, the first movement is to rise the leg, so the acceleration vector points upwards thus the great positive peak will be when the leg is in the maximum distance from ground. Then, there is a change of direction and it appears a negative peak in this trace. The immediate movement is to lower the leg and touch the platform, so when the patient puts his leg in the force plate there is a positive peak due to the acceleration vector pointing upwards again.3.15.

Now, we have to consider others aspects like the limbs with which the person starts to walk. To do all more comfortable for the patients, it was not specified with which leg they had to do the first step, so we have to determinate automatically this fact. To do this we calculate all interesting peaks in the right shank acceleration as well as left shank acceleration. Then, we identify first peak in time 3.10.

Other important aspect is to consider the sample frequency. The sample frequency is 120 Hz in force plate signals and 200 Hz in GaitWatch signals. Thus, we have to reshape the Force Plate signals to match other signals.

All the key parameters and signals are saved using Matlab's "time series" for adding descriptive information to the fact.

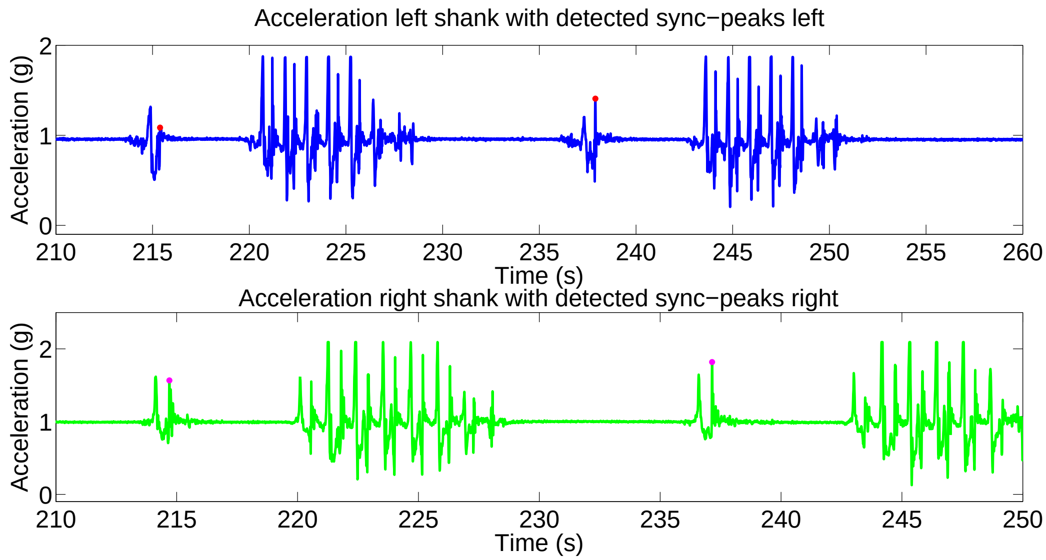

Figure 3.11: Peaks detected for the Synchronisation in the Accelerometer signals.

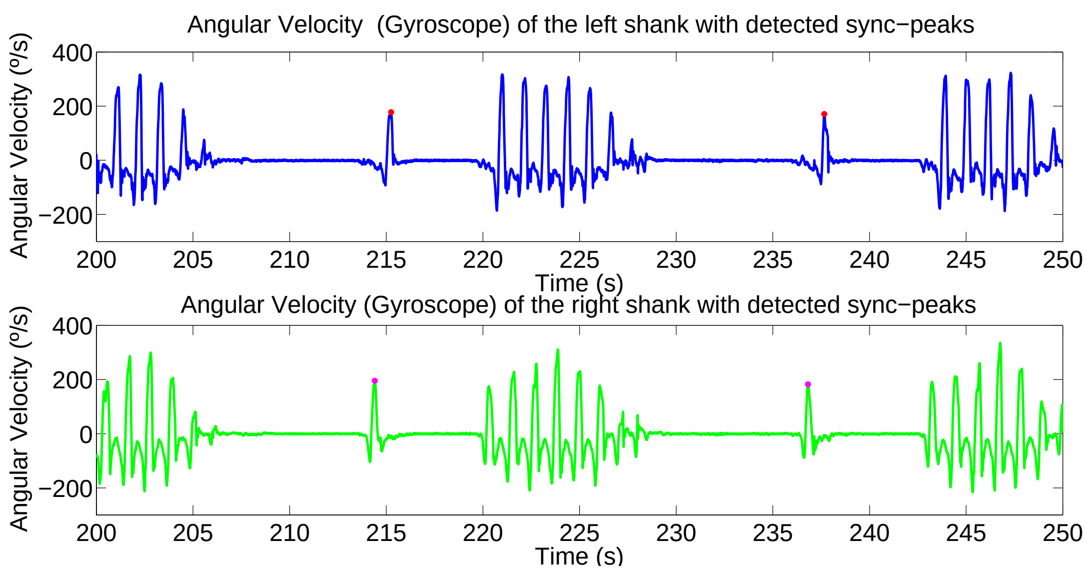

Figure 3.12: Peaks detected for the Synchronisation in the Gyroscope signals.

Finally, we compare the peak detection for the synchronisation between the accelerometer signals and the gyroscope signals. The behaviour of the gyroscope signal is clearer to the naked eye. We can sense there is a negative peak when the patient raises his leg to step. This is negative because the movement is upwards and the Z axis is pointing to the floor so the Angular Velocity is negative. The next positive peak of happens when the person touches the platform so this is the key point to use in the synchronisation3.12.

If we compare the behaviour of both signals, it makes sense because a peak of acceleration has to appear when there is a strong growth (or decrement) of the velocity, and this happens when the person moves up or down the limbs3.113.12.

The correlation between the peaks detected with both systems is very high and the difference between the locations of the peaks is very small as well. This indicates that it was done correctly and these detected points are suitable to do the synchronisation. We can see this in the folllowing figures:

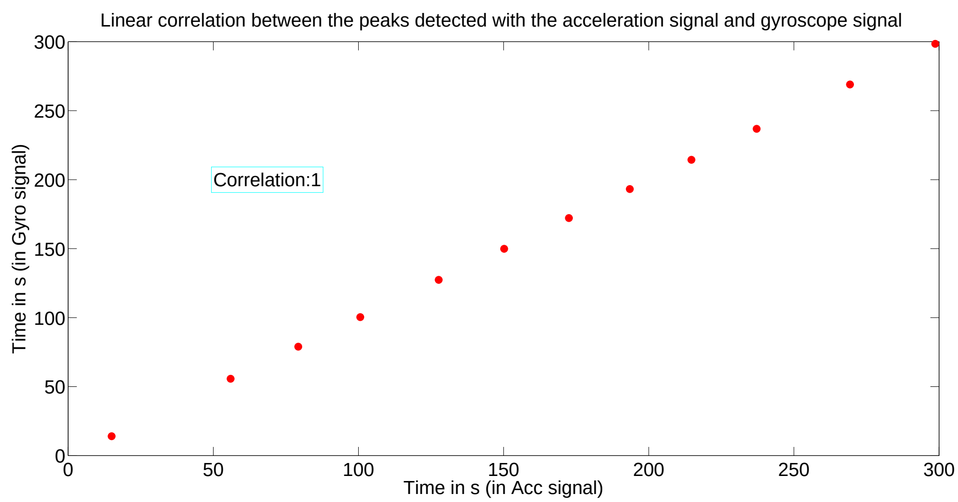

Figure 3.13: Linear Correlation between peak Acc and peak Gyro used for the synchronisation.

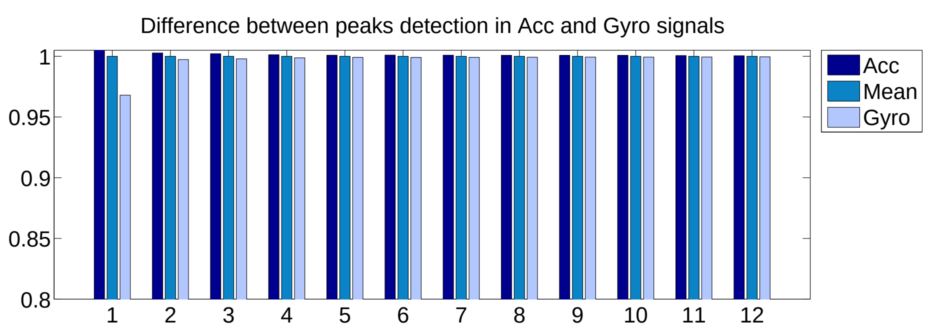

Figure 3.14: Comparison between points synchronisation detected with accelerometers and gyroscopes.

In 3.1 table we can see that the mean of the difference between the peaks detected with the accelerometer and gyroscope signals is less than 0.5 second in all cases, so it is very small. Also, the correlation between them is very high and the probability of no correlation is smaller than 0.05 which means that the correlation is significantly different from zero.

Table 3.1: Comparison between the peaks detected with accelerometer and gyroscope.

Patient	Average peaks difference	Corr	Prob
ES39	0.3438	1.0	1.096 e-13
RK55	0.3014	1.0	2.720 e-13
RS46o	0.2500	1.0	2.750 e-29
MM57	0.4970	1.0	3.480 e-26
WS42	0.3990	1.0	1.410 e-25
SW47	0.3615	1.0	2.190 e-25
TS40	0.2674	1.0	1.559 e-31

Finally, the results of the synchronisation can be seen in following figure:

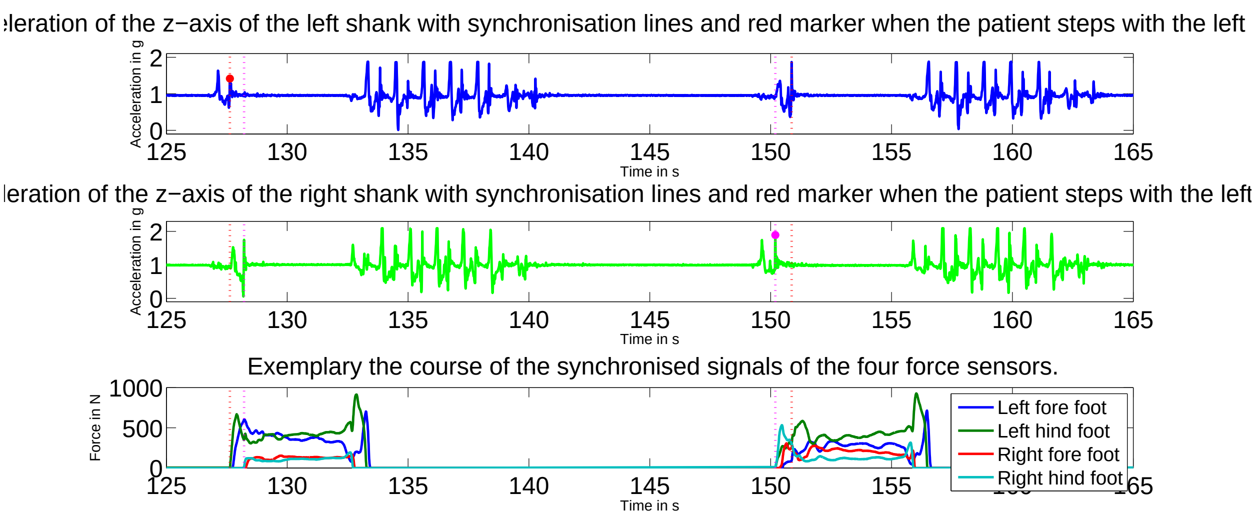

Figure 3.15: Synchronisation of the Force from the FP and Acceleration from the GW System
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3.4 APA analysis

3.4.1 Introduction and chapter's structure

Anticipatory postural adjustments (APAs) represent balance control that help to stabilise and mobilise the body based on anticipation of forces accompanying voluntary movement such as volitional lifting of the foot during step initiation [40]. Step initiation requires a tight proprioceptive coordination between motor commands for postural adjustments and for stepping, so APAs act to accelerate the center of pressure over the stance foot immediately prior to gait [10].

APAs, before gait initiation, are bradykinetic in advanced Parkinson's disease and may be one of the factors associated with 'start hesitation' [10].

Early identification in patients with PD is important because new neuroprotective medications are being tested to slow the progression of this disease and it is necessary to begin early in the disease, prior to significant loss of neurons [41].

Currently, the most common way to evaluate postural control in the clinic is to use clinical rating scales that are limited by clinician bias, insensitivity to mild impairments and poor reliability. These limitations are serious problems for clinicians and researchers who want to monitor the disease progression, determine intervention efficacy or treat people with mild balance deficits [41] .

Technology available for clinicians and researchers to mesure APAs is generally limited to a force plate for the analysis of the center of pressure. However, force plates are quite large and expensive and require a proper installation that may not be practical for clinical use. Thus, Body-worn accelerometers have been proposed as a portable, low-cost alternative to a force plate for measurements of postural sway [41] .

Therefore, along this chapter we will do a comparative study of the measurements obtained using the force plate as well as accelerometers that make up the Gait Watch system. Also, we will compare these measurements with gyroscope data that form part of this system too, in order to determine what sensors give us the more accurate results.

3.4.2 FP and GW Signals

As we said in the previous chapter, leg's acceleration in the Gait Watch System as well as force in the Platform System are the most accurate signals to detect when the step happens. This is very important to do the synchronisation of the all signals of the system. However, the most interesting signals from a medical point of view are the trunk acceleration and the displacement of the center of pressure.

This is because we can observe the Anticipatory Postural Adjustments in these signals, i.e the body movements before stepping. According to prior studies and priori criteria it is thought that it could be a good way to characterise the APAs. Therefore, the first process to carry out is the analysis of the trunk acceleration and COP to determine if there is some pattern and whether we will be able to use them to obtain information about the patients.

The first step that needs to be carried out is to establish the axes in the platform to define the position over it. The X axis points forward, not existing negatives values because the range is between 0 and 510 mm, that is the platform's dimension in this direction. The Y axis is pointing to the right of the patient, so the positive values indicate a movement toward right with regard to the midline. Comparably, the negatives values are found when the movement is toward the left 3.16.

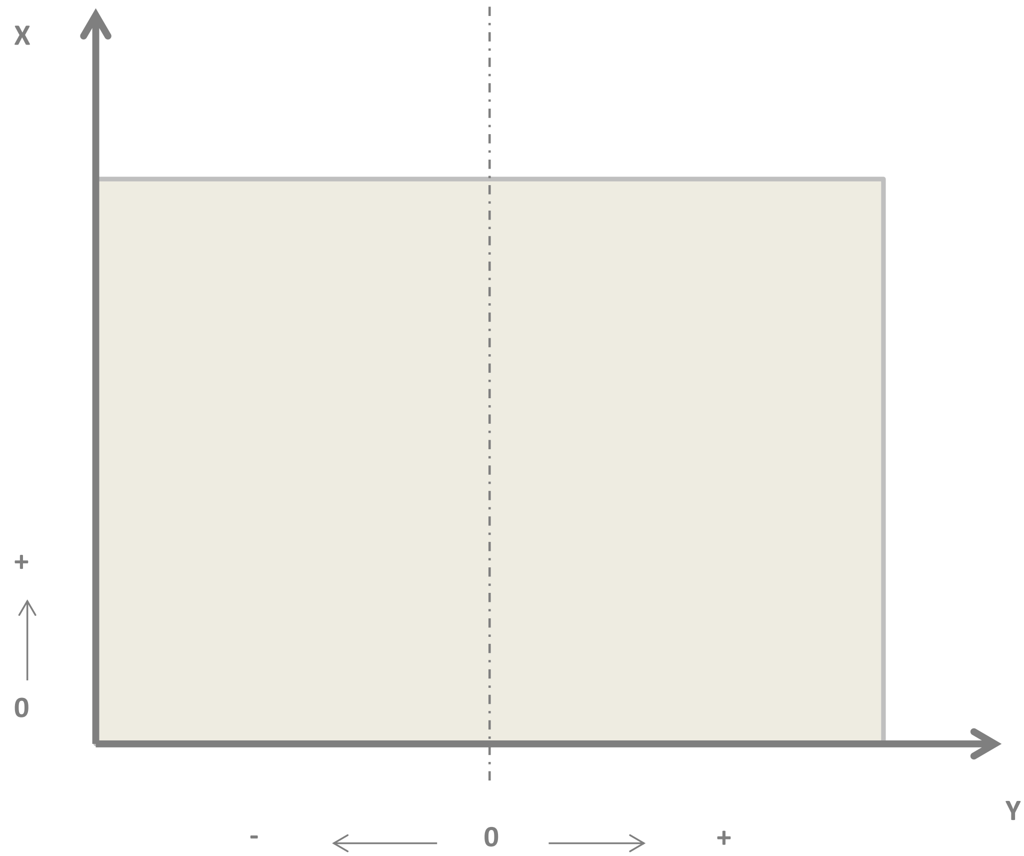

Figure 3.16: Definition of the axes in the Platform.

Now, for the GaitWatch System we have to determine the orientation of the axes of the body frame that we wish to use, as well as the orientation of the rotation around those axes. The most popular configurations is to set the X axis pointing forwards, the Y axis pointing to the right and the Z axis pointing down. This configuration follows the rule of the right hand for the orientation of the axes and the corkscrew rule for the rotation [4].

Since we will be using the GaitWatch device to monitor gait, then we need its X axis to point to the front of the patient, the Y axis pointing to the right of the patient, and the Z axis to the floor 3.17 [4].

Once we have identified the axes of the accelerometers, we now proceed to identify the axes of the gyroscopes and their orientation. By convention, as it is depicted in 3.17, the sense of the rotation around a given axis is positive when the axis is pointing forwards (from the perspective of the user) and it is turned to the right. So, in this case the rotation is positive toward right3.17. Analogously, the rotation is negative when it is turned to the left.

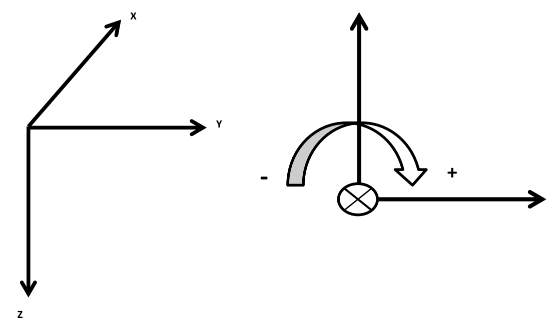

Figure 3.17: Definition of the axes in the accelerometers ans gyroscopes (left). Orientation of the axis rotation in gyroscopes (right).

We have to differentiate between the front-back movement and the right-left movement. In the first one, we have the acceleration in X axis and the Antero-Posterior COP. In the second one, the movement is traced by the acceleration in Y axis and the Medio-Lateral COP.

Whether we focus in the Antero-Posterior movement, the body is displaced forward while the step is being completed. Thus, the center of mass is shifted backward in this period of the movement. In the case of the center of pressure, we can find first movement backward to gain momentum and after that COP moves forwards under the stance of the foot 3.18.

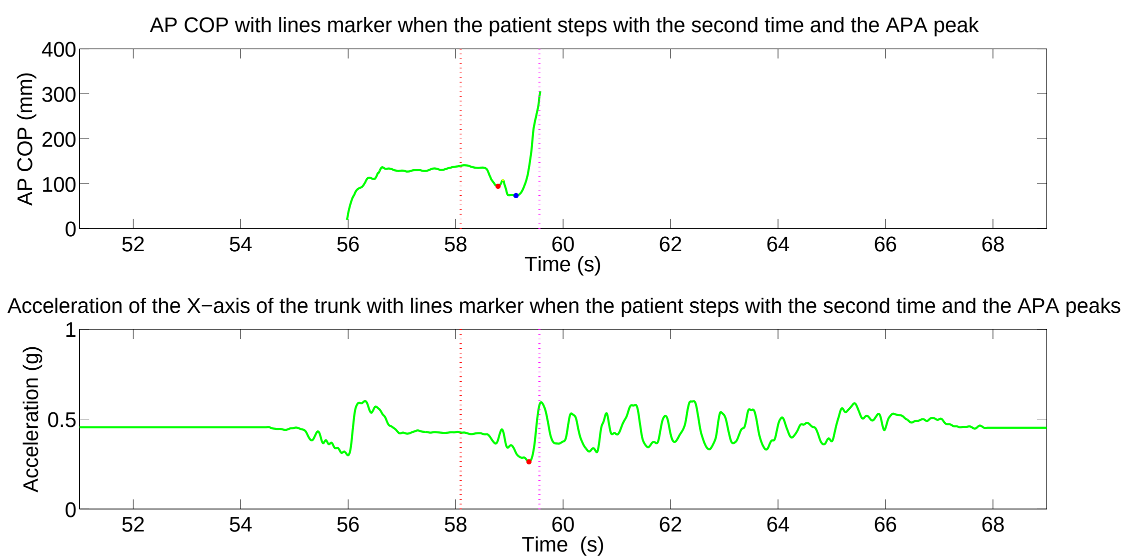

Figure 3.18: COP and acceleration in Antero-Posterior direction.

From a kinematic point of view, the trunk is moved anteriorly while the patient steps.

Therefore, there will be a peak of acceleration in the X axis pointing forward, so we will find a 'negative' peak at this moment because the acceleration vector points in the opposite direction to the movement. After that, there is a positive peak that corresponds with the direction change just when the step finishes.

Also, we can observe a pattern due to all movements before stepping follows a single trace approximately. The pattern of the acceleration in the X-axis (anterior-posterior movement) is always the same, regardless of the leg with which the patient starts to walk.

Moreover, we discern differences in the Medio-Lateral direction regarding the foot with which the step is done.

If the patient starts to step with the right foot, the center of mass is accelerated towards the left because the majority of the body weight is located in the foot over the ground. However, the center of pressure is shifted toward right and then the COP displaces medio-laterally to left, toward the foot is contact with the ground. For the acceleration in the Y axis, there is a negative peak because the movement is towards right and the acceleration vector points in the opposite direction, with negatives values. After this, we find a negative peak due to the change of direction3.19.

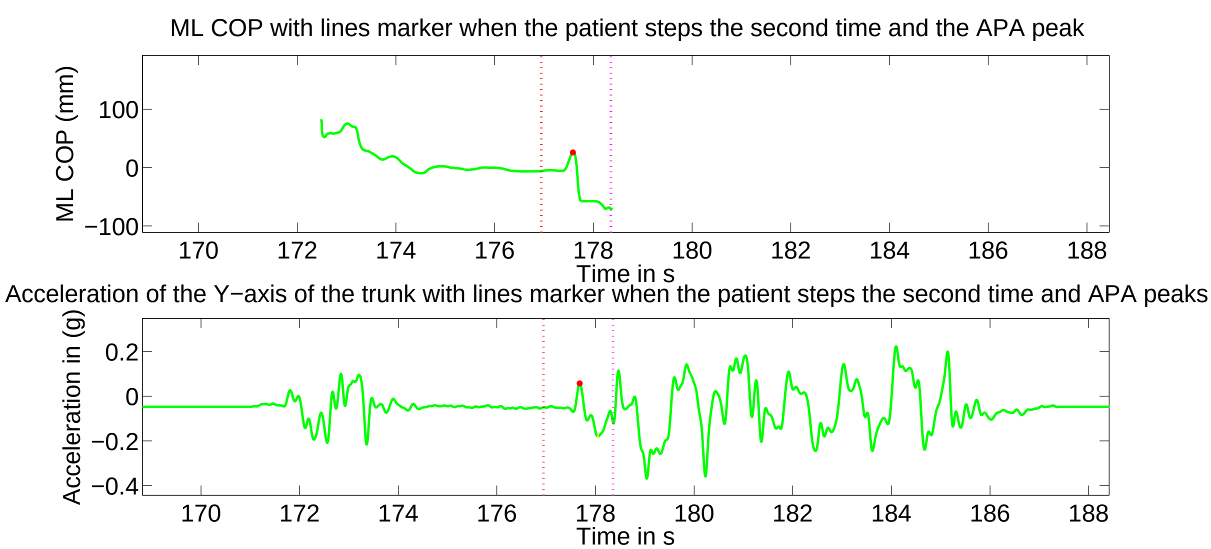

Figure 3.19: COP and acceleration in Medio-Lateral direction when patient steps with the right foot.

If the patient starts to step with the left foot, the movements are the same than in the prior case unless the movement directions are just the opposite. We can perceive this in 3.20

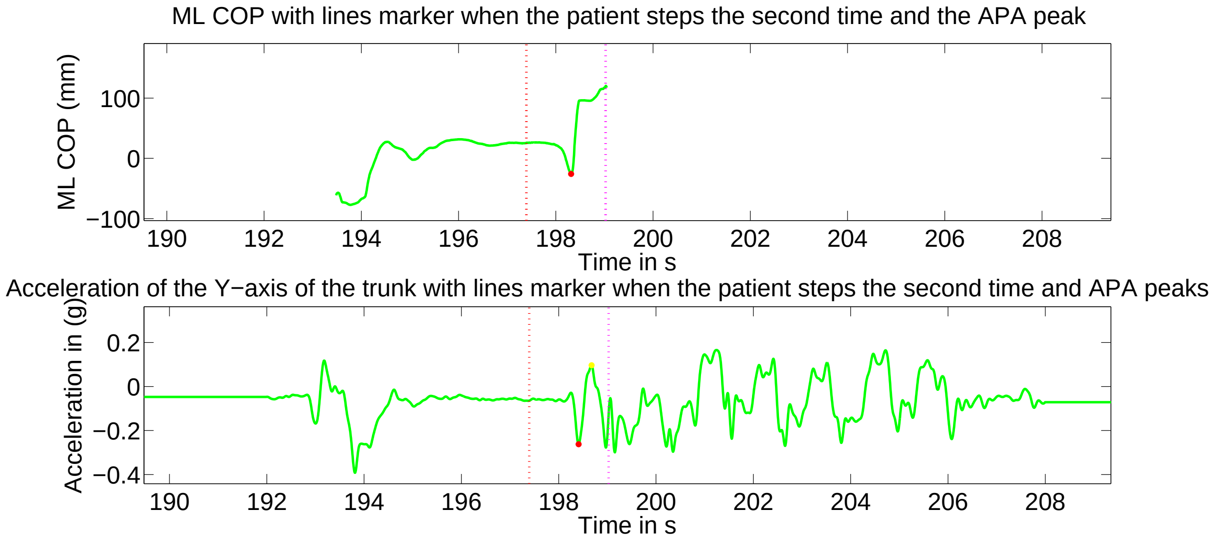

Figure 3.20: COP and acceleration in Medio-Lateral direction when patient steps with the left foot.

To sum up, we have to differentiate between the foot with which the step is done (stepping foot) and the foot over the ground (stance foot) to understand the behaviour of the APAs. The center of mass (COM) is shifted toward the stance foot to maintain the equilibrium during the balance phase. The center of pressure (COP) is divided in different phases. Firstly, the COP moves towards the stepping foot and backwards to generate the momentum to step (S1 period). Hereafter, the COP is displaced toward the stance foot. This happens at time when the other foot is in the air (S2 period). Finally, the COP moves forward and under the stance foot (S3 period) 3.21.

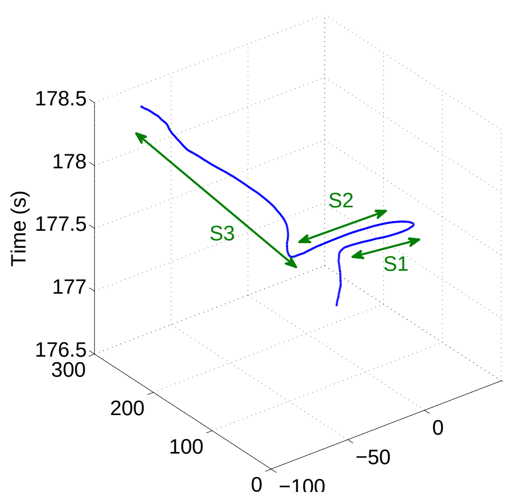

Figure 3.21: Trajectory of COP when patient steps with the right foot.

Bearing in mind the same phases for the acceleration than in the above case, in the first period (S1 period) the body is accelerated forwards while the momentum is generated to step. After, the trunk is slightly accelerated towards the left (S2 period) and finally, in the last period the body is moved fordwards and to the right to complete the step (S3 period) 3.22.

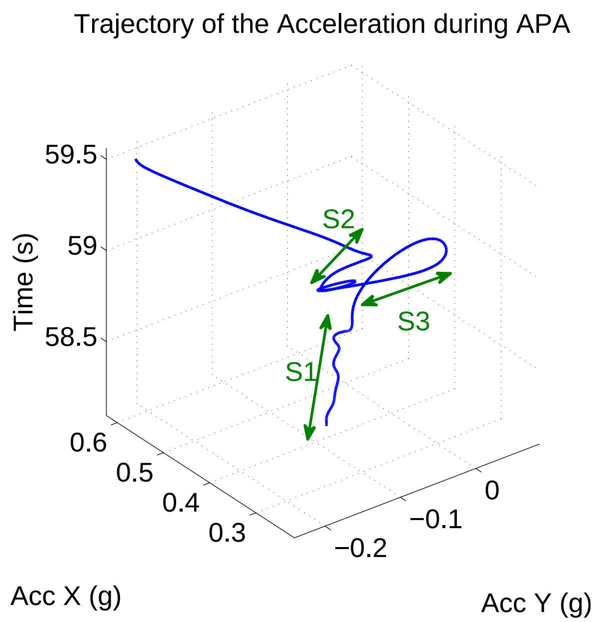

Figure 3.22: Trajectory of acceleration when patient steps with the right foot.

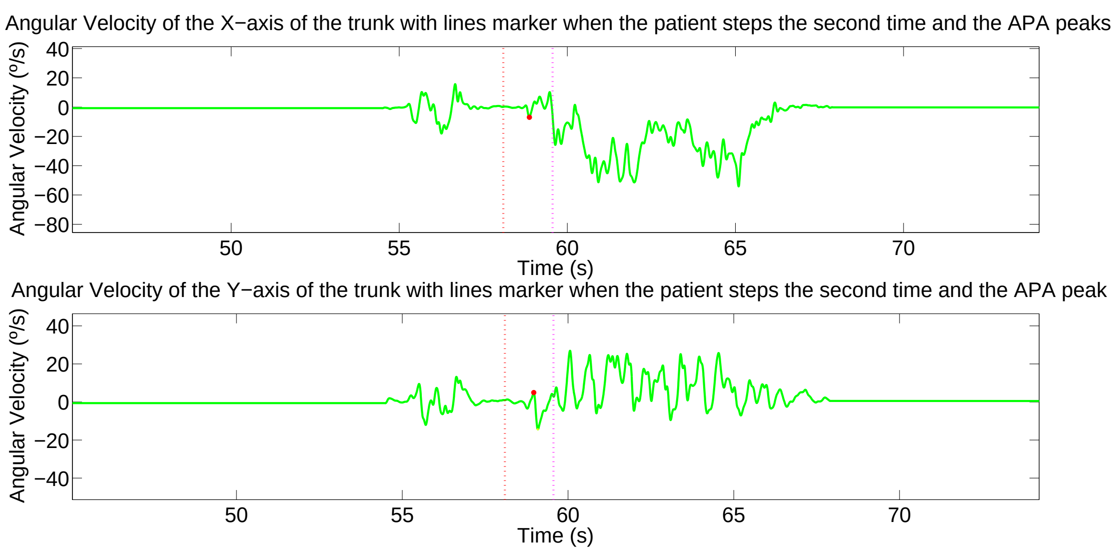

Figure 3.23: Angular Velocity when patient steps with the right foot.

The behaviour of the gyroscope signals is very similar to the accelerometer signals but in this case we are measuring a turn forward or backward and to the right or the left.

There are a negative peaks when patient turns to backward before walking in the Antero-Posterior direction. Besides, there will be a negative peak when patient is shifted towards the right and positive in the case that the turn was done to the left in the Y axis.

3.4.3 PCA

One of the biggest difficulties inherent in multivariate statistics is extracting features to obtain the most relevant information from the original data and represent that information in a lower dimensionality space.

PCA is a qualitative rigorous method for achieving this and it has been widely applied in gait analysis both for the reduction of redundant information and the interpretation of multiple gait signals [42].

This method attempts to represent the data efficiently by decomposing a data space into a linear combination of a small collection of bases consisting of orthogonal axes that maximally decorrelate the data [31].

Given a set of centered N-dimensional training gait samples $x_j, j = 1, ..., Mx \in$ such that R_N and $R = \sum_{k=1}^{M} x_j = 0$

Where M represents the number of gait samples and N is the number of input values. The x_j vectors are aligned in the data matrix X. Also, the data have to be centered so it is necessary to extract the average of the each set.

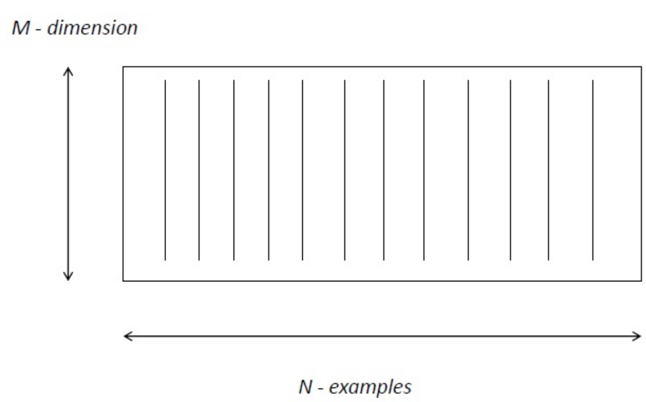

Figure 3.24: Data matrix X with M rows and N colums.

The projection of the *j-th* vector x_j onto the vector *'u'* can be calculated in the folowing way:

$$p_j = \overrightarrow{u}^T \overrightarrow{x}_j = \sum_{i=1}^{N} u_i x_{ij} \tag{3.2}$$

We want to find a direction *'u'* that maximizes the variance of the projections of all input vectors. That function to maximize is:

$$J^{PCA}(\overrightarrow{u}) = \sigma^2(p_j) = \frac{1}{M} \sum_{j=1}^{N} (p_j - \bar{p})^2 = ... = \overrightarrow{u}^T C \overrightarrow{u} \tag{3.3}$$

Where C is the covariance matrix of the data matrix X.

$$C = \frac{1}{N} \hat{X} \hat{X}^T$$

Using the technique of Lagrange multipliers, the solution to the maximization problem is to compute the eigenvectors and eigenvalues of the covariance matrix.

Thus, we have to solve the following eigenvector problem:

$$\Lambda U = C' U \tag{3.4}$$

In such a way the orthonormal matrix U contains the eigenvectors $u_1, u_2, ...u_N$ in its columns and the diagonal matrix Λ contains the eigenvalues $\lambda_1, \lambda_2, ..., \lambda_N$ on its diagonal.

The eigenvalues and the eigenvectors are arranged with respect to the descending order of the eigenvalues, thus $\lambda_1 \geqslant \lambda_2 \geqslant ... \geqslant \lambda_N$

Therefore, the most variability of the input random vector is contained in the first eigenvectors. Hence, the eigenvectors are called principal vectors.

So U can be used as a linear transformation to project the original data of high dimension into a space of lower dimension.

$$P = U^T \bar{X}$$

In terms of gait, feature extraction by choosing the first two eigenvectors, PCA can directly perform the dimensional reduction[31]. We can use this new information to do a classification. The classification can be achieved through a SVM which separates a given set of labelled training data with a hyperplane that is maximally distant from the two classes [33].

3.4.4 Feature extraction

Automated recognition of gait pattern change is important in medical diagnostic. Thus, in this section we are going to extract and evaluate different gait features as well as methods to obtain them. Feature extraction is important to do a good classification of patterns. The main goal in this chapter is to obtain the relevant information from the platform and inertial sensors synchronised previously and carry out a comparative study between them.

One the one hand we try to figure out whether there is a correlation between the features of both systems and determine if we can use the inertial sensors to characterise the movement without another auxiliary measurement platform. One the other hand we want to extract useful features that we can use to do a classification between patients and therefore it can be used for diagnosis.

To do this, we will use the data obtained after the synchronisation between Force Plate and Gait Watch signals. Using this signals lets us extract the information easily and compare them.

The next step is to determine when the second step happens. We used as a reference the point when the patient touched the platform to do the synchronisation. However, in this case we have to identify when patient carried out the second step to go down from the platform. We need this part of the signals because it is when we can see the displacements of the center of pressure. To obtain these limits of the signals we use the LTSD algorism. This is applied over the acceleration signal so we can determine the beginning of this period for each cycle. The end of the interval is the point when the patient goes down and touches the ground ,i.e when there is not pressure signal over the platform. Thereupon, we apply a low pass filter to the Gait Watch signals, i.e signals of the accelerometers and gyroscopes in the trunk. This allows us to delete the low frequencies of these signals due to the noise of the sensors and get the features properly. Specifically it has been used a low pass filter with a cutoff frequency of 2 Hz.

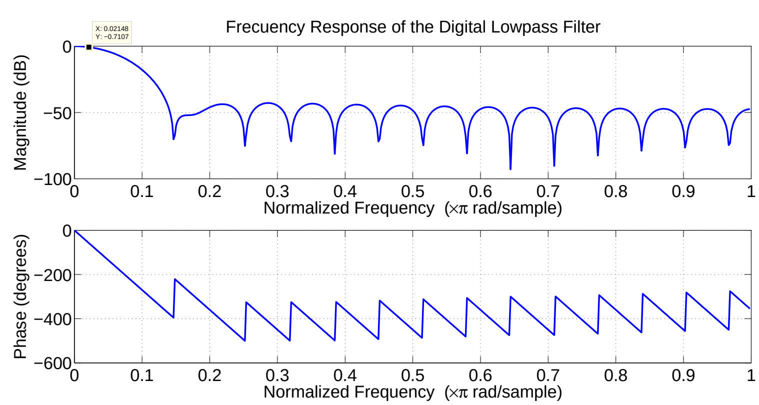

Figure 3.25: Lowpass Filter with a cutoff frequency of 2Hz

One the signals have been filtered, we will do the average of all repetitions. Typically, the experiment is repeated several times to do a ratio and obtain a single signal for each patient. As we said before, the protocol is repeated about ten times so we have to synchronise this cycles and realise the mean of all them. First of all, we need to determine when the patient steps with the right of left foot. This is important for the signals in the medio-lateral direction because the sign of the signals is the opposite. Thus, if patient does the step with the left foot, the signal will be inverted before doing the mean. This fact is detected seeing the last values of the center of pressure because this gives us information about the localization of the feet. When the patient starts to step with left foot, last value of the cycle of ML- COP is positive because the step finishes the pressure which is located in the right foot. However, if the patient starts with right foot, the last value of the ML-COP cycle will be negative.

To align the signals, we use cross-correlation between them. The cross-correlation is a measure of similarity for two signals as a function of the lag of one relative to the other [43]. For a discrete function as in our case, the cross correlation is defined as:

$$(f * g)[n] = \Sigma_{m=-\infty}^{\infty} f^*[m]g[m+n] \tag{3.5}$$

Where f^* denotes the complex conjugate of f and n is the lag.

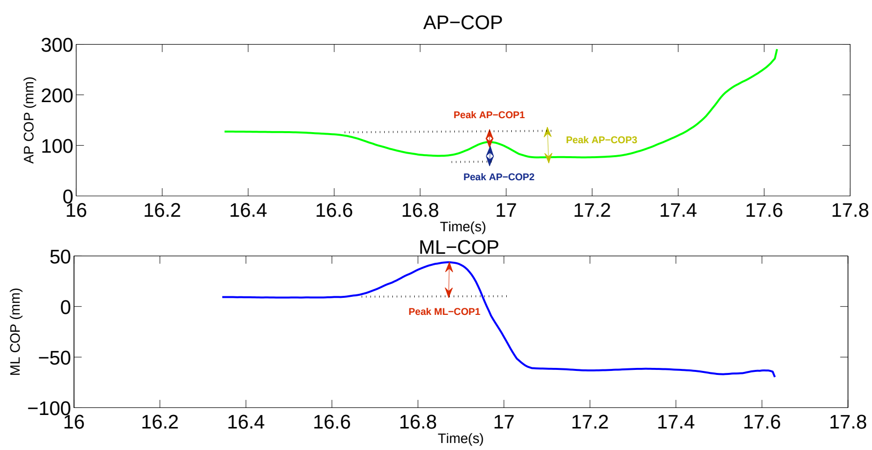

Figure 3.26: Peaks in the Center of Pressure signals .

Using this method, we can determine the point where the signals are more similar. After this, we can interpolate them and carry out the average between them.

At this point, we have six signals per patient: the center of pressure in the antero-posterior and medio-lateral direction, the acceleration in X and Y axis and the angular velocity in the same axes. Therefore, the next step is to extract the features of them.

We have analised the Gait Watch and Forceplate signals in the above chapter and determined the most interesting episodes in these signals. So, the first features that we will obtain are the peaks in COP, acceleration and angular velocity. We can see this in figures 3.26-3.28.

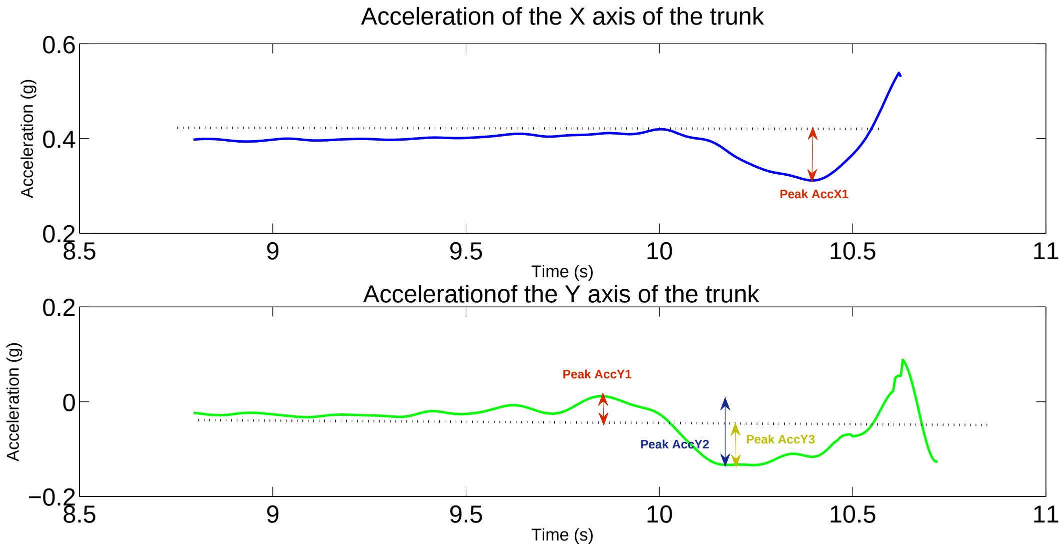

Figure 3.27: Peaks in the Acceleration signals .

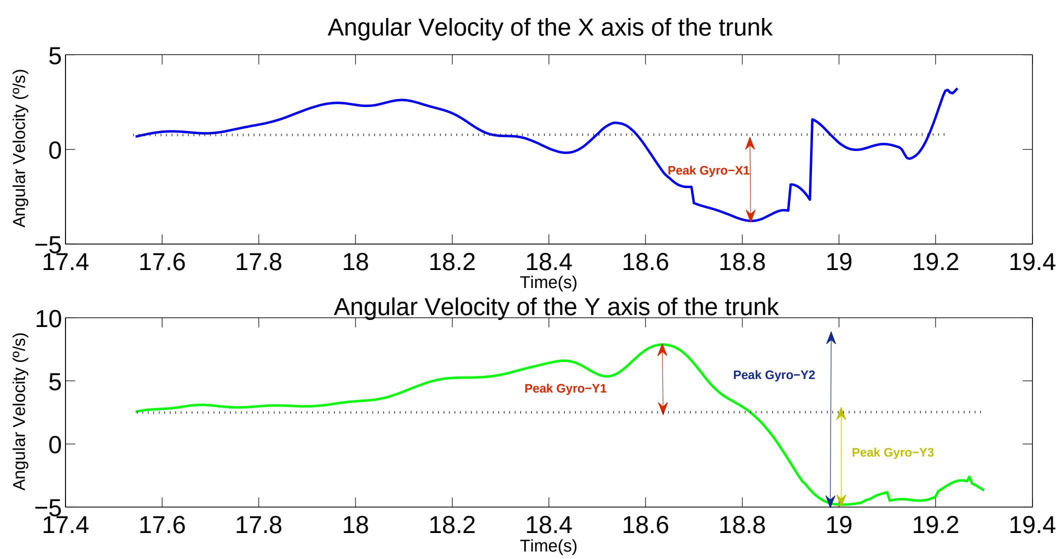

Figure 3.28: Peaks in the Gyroscope signals.

Hereafter, we will calculate the APA duration in each system because it would be able to be an appropiate parameter to compare. Also, the majority of these features have been used in others studies [10] so it can be a right way to measure the movement.

Now, we are going to apply PCA algorithms to obtain the most significant information about human movement. This method allows us to minimise the redundant information performing the dimensional reduction.

We applied PCA twice: in the signals of the Antero-posterior direction (AP-COP, X-Acc and X-Velocity) and of the Medio-lateral direction (ML-COP, Y-Acc and Y-Velocity). So far, we have the projection in the orthogonal space, three eigenvectors and three eigenvalues. The corresponding eigenvectors are ranked in a descending order of eigenvalues and by choosing the two first eigenvectors PCA directly performs the dimensional reduction, that is, the class of three dimensional gait data is described by low-dimensional features containing only two principal components.

The two first eigenvalues of the covariance matrix account for 98% of the variance. This indicates that we only need to take the two first eigenvectors to have the significant information of the data. Also, if we see 3.29 and 3.30 we can determine that the important information, i.e the information with more variance is defined with the COP and Angular Velocity signals. This is because the acceleration and angular velocity signals are very similar and one of them is not necessary, i.e it does not provide us with additional useful information.

The next step is to obtain the same features of the new signals. Now, we have four signals per patient: two components for AP direction and two more for ML direction. The characteristics extracted in this case are the same than with the originals signals.

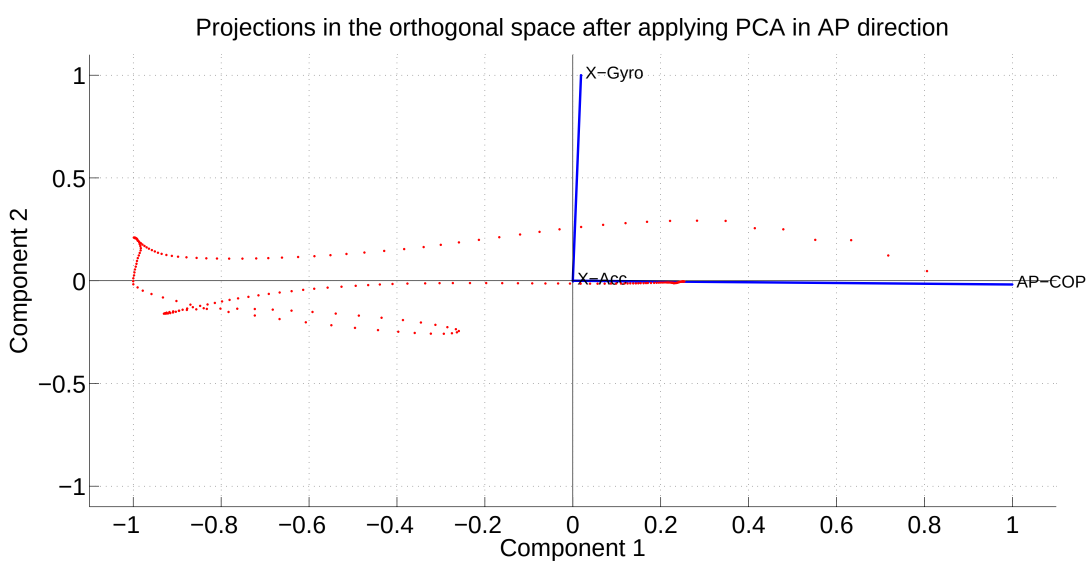

Figure 3.29: Projections in the orthogonal space after applying PCA and eigenvectors in Antero-posterior direction.

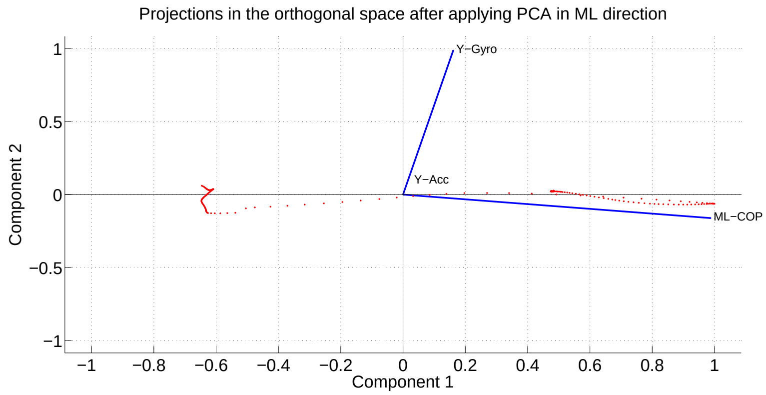

Figure 3.30: Projections in the orthogonal space after applying PCA and eigenvectors in Medio-Lateral direction.

Finally, we apply PCA between patients. Our data base is reduced because we only have five patients. So, our matrix data has five columns where each one has the COP, Acceleration and Angular Velocity concatenated. As in the above study, the two first components account the most of variability and this representation in the space indicates us the movement relation between patients, i.e whether the movement is similar between them. This allows us to know if it is possible to do a classification afterwards and what components are appropriated to do it. In the Antero-Posterior direction, the projections are located in the right part of the orthogonal space. People analysed in this study are patients with different level of the disease. Therefore, the second component would be able to be useful to differentiate patients with parkinson's disease. Also, it is possible that the first component can be used to differentiate between control subjects and do a classification 3.31.

In the Medio-Lateral direction the data are more dispersed. This indicate that the movement changes a lot between patients. However, almost all eigenvectors are pointing toward the upper half of the space3.32.

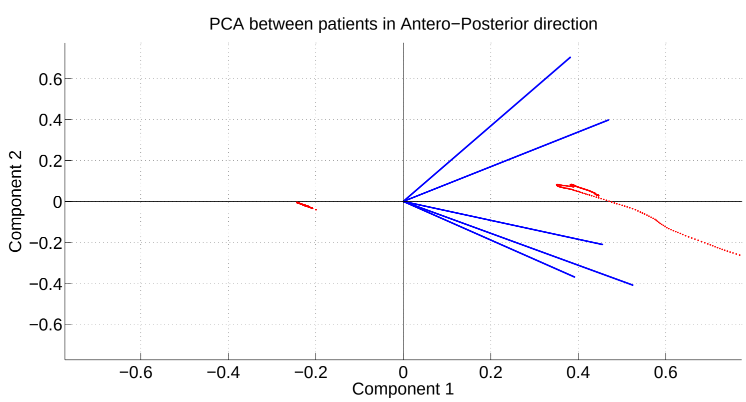

Figure 3.31: Projections in the orthogonal space after applying PCA and eigenvectors in Antero-posterior direction between patients.

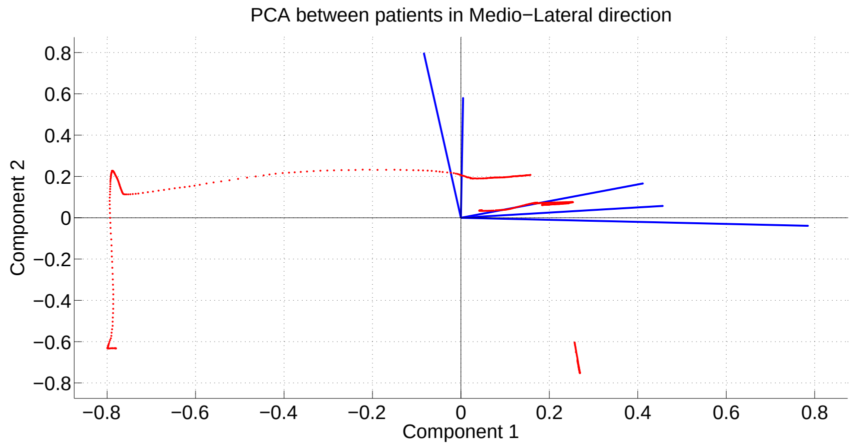

Figure 3.32: Projections in the orthogonal space after applying PCA and eigenvectors in Medio-Lateral direction between patients.

3.4.5 Results discussion

Once the APA features have been calculated, we will do the correlation between them. Firstly we are going to do a comparative study between FP and GW in the Antero-posterior direction. We calculated the correlation between the APA peaks detected in the COP signal 3.26 and the the peak calculated in the acceleration and angular velocity signals 3.273.28. The results of this correlation are showed in 3.33. If we analyse these values of correlation, we can determine that the features of the gyroscope have a higher correlation with the features of the COP signal. The first peak of the COP and the peak of acceleration and angular velocity signals account for a positive correlation with a significant value. Also, in the center of pressure, the most interesting feature is the first peak, i.e when patient has momentum to step because the correlation with the acceleration signal as well as the angular velocity achieve the highest values.

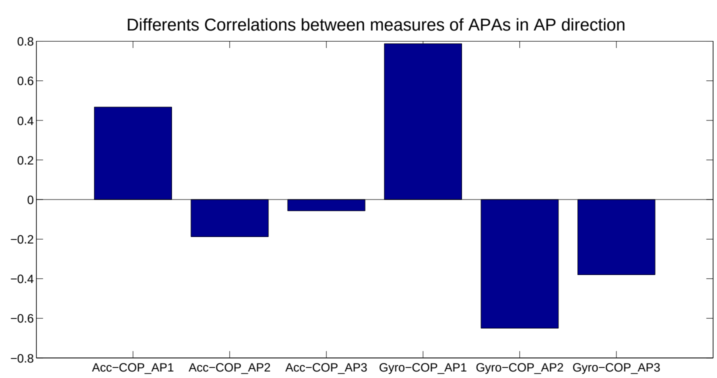

Figure 3.33: Correlation between features in the AP direction.

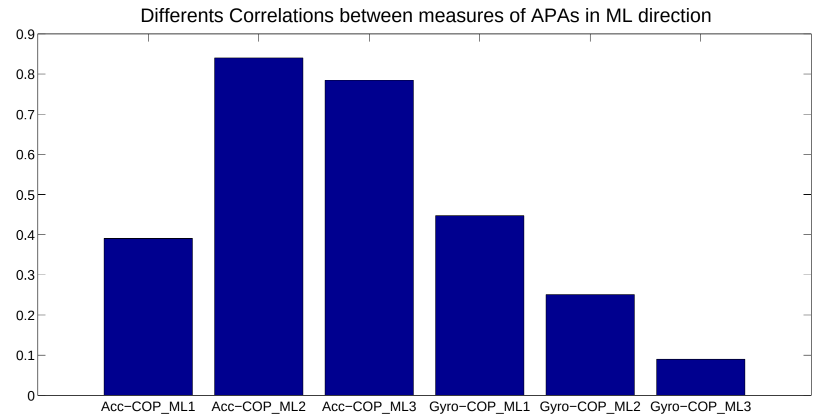

Figure 3.34: Correlation between features in the ML direction.

Then, we will compare these signals in the medio-lateral direction. In this case, all correlations are positive and a lot of them with a considerable value. However, we can identify that the most interesting signals in this direction are the signals from the accelerometers. We did the correlation between the peaks detected in the ML-COP and the rest of the features obtained from the acceleration and angular velocity signals. Therefore, the most interesting features of these signals are the height of the negative peak as well as the distance between both peaks in the signals 3.34. The correlation is higher than 0.8, so this indicates that the accelerometers can give us useful information as the center of pressure.

If we pay attention to the APA duration3.35, the correlation between COP and Acceleration and COP and Angular Velocity is negative. This doesn't make sense because it should be positive. Thus, we determine that there is not correlation between them. Even so, there is correlation between the APA duration in accelerometers and gyroscopes.

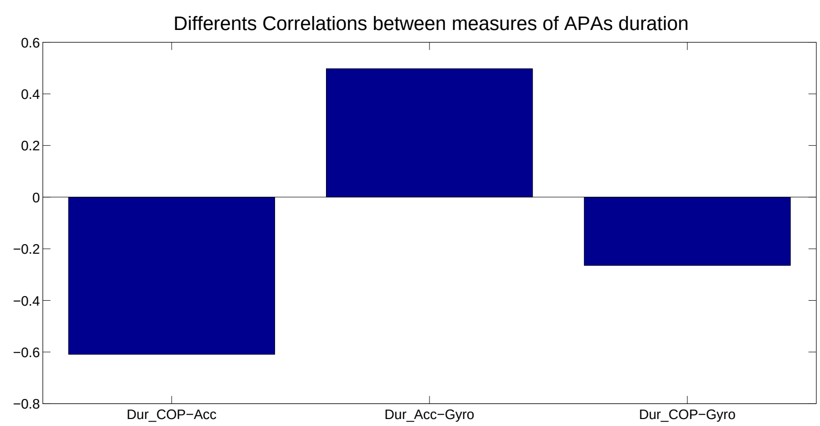

Figure 3.35: Correlation between APA duration.

Finally, we are going to see the correlation after using the PCA method. In principle, these features are more accurate because we removed the useful information and we have less and more interesting data. Whether we observe 3.36, the first three values are the correlation between the three APA peaks detected in the first component (analogous to COP signal) and the APA peak of the second component (analogous to angular velocity or acceleration signal) in the AP direction. The most significant value is the correlation between the negative peak in the first component and the peak of the second component.

In the ML direction, we do the correlation between the APA peak of the first component and the three features of the second component. The highest values are the correlation between the peak of the first component and the distance between both peaks of the second component being this a negative correlation3.36.

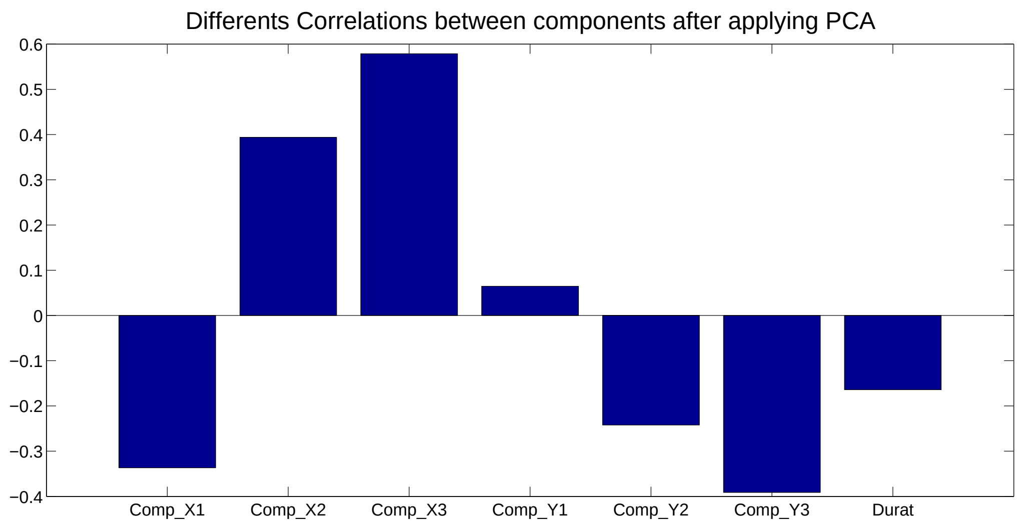

Figure 3.36: Correlation between features after applying PCA.

Chapter 4

Signals processing and classification of data force

4.1 Introduction and chapter's structure

In the previous chapter, we analysed and extracted features of force data and inertial sensors data of the patients from the same experiment. Thus, once we compared both systems and determined the relationship between them, we proceed to conclude whether we can classify force data from patients and control subjects.

Along this chapter, we are going to explain the hardware used in this experiment, the procedure to gather the data, the process carried out to calculate the relevant signals, different techniques to feature extraction as well as the results obtained after the classification of this information.

4.2 PLS

Partial least squares regression (PLS regression) is a statistical method that bears some relation to principal components regression; instead of finding hyperplanes of minimum variance between the response and independent variables, it finds a linear regression model by projecting the predicted variables and the observable variables to a new space [34].

This algorithm is based on linear transition from a large number of original descriptors to a new variable space based on small number of orthogonal factors (latent variables), i.e factors are mutually independent (orthogonal) linear combinations of original descriptors [34] .

We used the PCA algorithm in the last chapter to extract features of the gait data. This new method is very similar but there are clear differences. Both PCA and PLS are used as a dimension reduction methodology. However, PCA is applied without the consideration of the correlation between the dependent variable and the independent variables, while PLS is applied based on the correlation. Therefore, we call PCA as an unsupervised dimension reduction methodology, and call PLS as a supervised dimension reduction methodology, i.e it has a phase of training and another of evaluation or testing[34].

Once we have explained the most important differences between them, we are going to explain the fundamentals of this algorithm. Assume X is a $n{\times}p$ matrix and Y is a $n{\times}q$ matrix. The PLS technique works by successively extracting factors from both X and Y such that covariance between the extracted factors is maximized. In our particular case, we will assume that we have a single response variable i.e., Y is $n{\times}1$ and X is $n{\times}p$, as before.

$$Y = UQ' + F$$

$$X = TP' + E$$

where Q*(qxr)* and P *(pxr)* are the matrices of coefficients (orthogonal loading matrices), F *(nxq)* and E *(nxp)* are the error term and, U *(nxr)* and T *(nxr)* matrices that are, respectively, projections of X and projections of Y.

Decomposition is finalized so as to maximize covariance between T and U. All algorithms to solve this follow an iterative process to extract the T(X-scores) and U(Y-scores) [34].

The factors or scores for X and Y are extracted successively and the number of factors extracted *(r)* depends on the rank of X and Y. In our case, Y is a vector and all possible X factors will be extracted. Each extracted X-score are linear combinations of X. Thus, the score T of X is of the form:

$$T = XW$$

Where W is a matrix obtained as follow:

$$W = conv(X, Y);\ W = W/||W||$$

With r (latents variables) columns.

4.3 Signals processing and feature extraction

The database used in this experiment is different in contrast with the above case. This database contains measurements of gait from 27 patients (mean age: 66.3 years; 63 % men) and 18 healthy controls (mean age: 66.3 years; 63% men). The database includes the vertical ground reaction force records of subjects as they walked at their usual. They wear underneath each foot 8 sensors [44] that measure force as a function time. The output of each of these 16 sensors has been digitized and recorded at 100 samples per second.

Once data have been gathered while subjects were walking during two minutes approximately, we read this information from the text file. This file contains the force of each sensors as well as the sum of force of the right and left feet.

With these values, we can obtain the center of pressure Antero-Posterior and Medio-Lateral as indicated the equation 3.1. To do this, we have to define the position of the sensors. When a person is comfortably standing with both legs parallel to each other, sensor locations inside the insole can be described (according to [44]) as lying approximately at the following (X,Y) coordinates, assuming that the origin (0,0) is just between the legs and the person is facing towards the positive side of the Y axis:

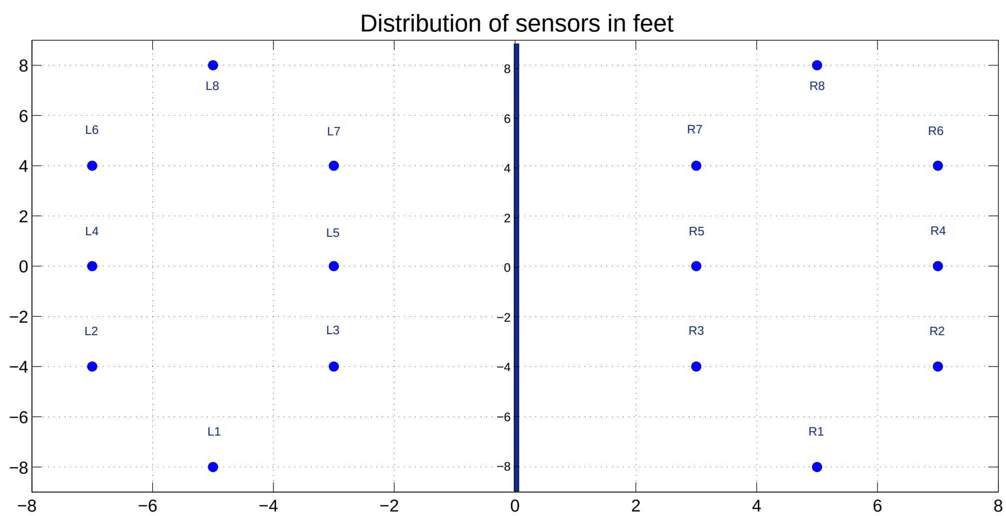

Figure 4.1: Distribution of the sensors underneath both feet.

The X and Y numbers are in an arbitrary coordinate system reflecting the relative (arbitrarily scaled) positions of the sensors within each insole. During walking, the sensors inside each insole remain at the same relative position, but the two feet are no longer parallel to each other. Thus, this coordinate system enables a calculation of a proxy for the location of the center of pressure (COP) under each foot.

Hereafter, we separate the different steps because the subjects carry out several steps during the experiment. We detect this when the COP signal has a strong fall in one of the feet. Once we have delimited the intervals of the signals, we figure out the average of them using cross correlation to synchronise the cycles properly. We can see the result in the following figure:

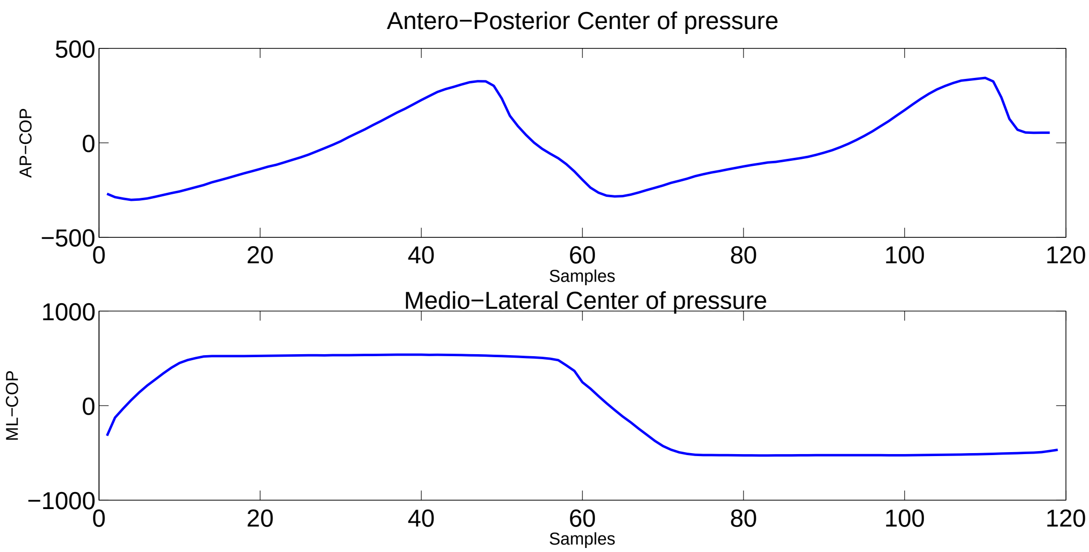

Figure 4.2: Center of pressure in AP and ML direction.

Thus, after this, we only have two signals ML and AP COP that represent one step of the patient. It is not absolutely necessary but it allows us to obtain an average of each repetition, being this more appropriated to characterise the subjects.

We use these signals to apply PCA as in the previous experiment. We match ML-COP and AP COP in the same column corresponding to the same subject and rearrange both patients and healthy controls in the same data matrix to apply this algorithm.

As we explained before, PCA is an unsupervised method 4.3, so we will use the PLS algorithm to extract the relevant information and carry out other type of classification of the data. We calculated X-score of all the data for different numbers of components (latent variables). The results after the classification can be seen in the next section.

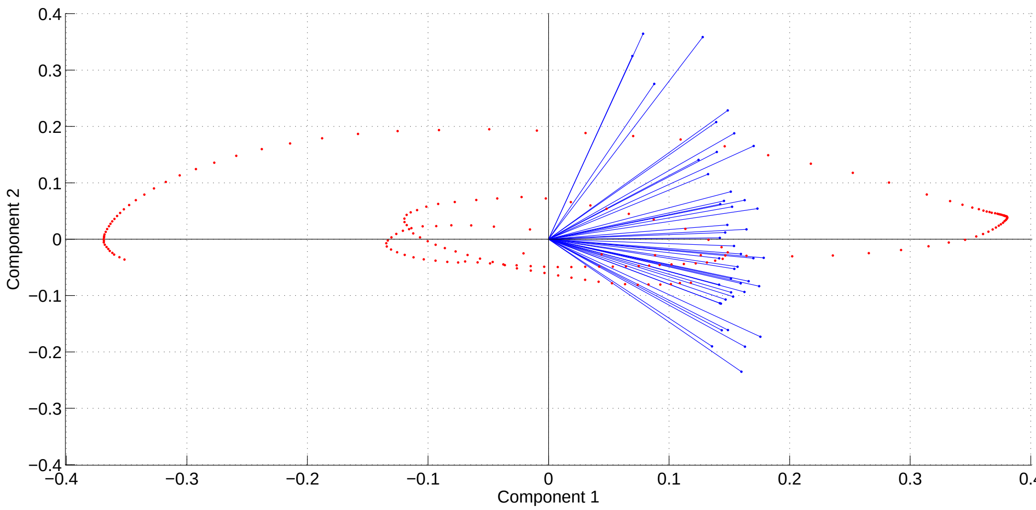

Figure 4.3: PCA applied for all subjects

We can represent the mean of the original data as well as the sum of the signal obtained after applying PCA and PLS algorithms.

We calculate the sum of these components because it allows us to see the areas in the signal where there is more variance.

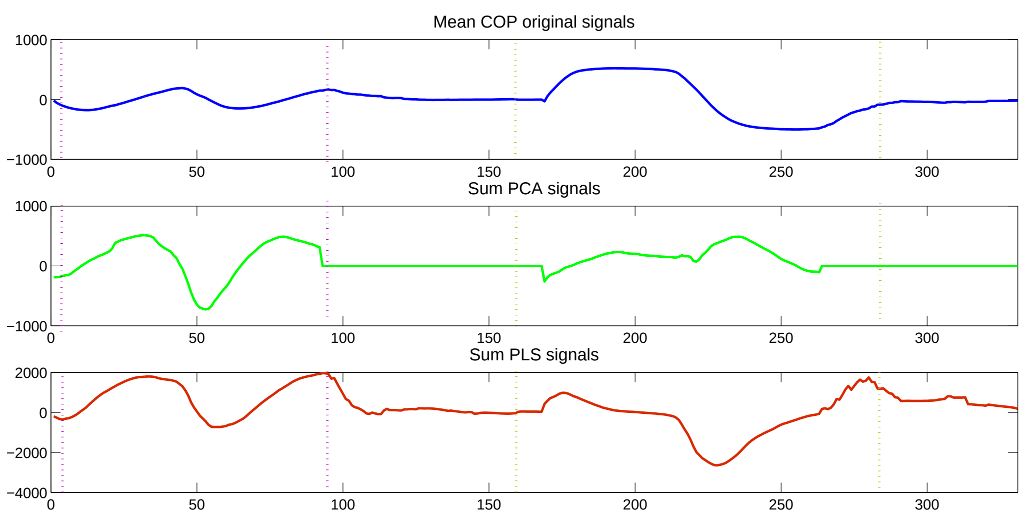

Figure 4.4: PCA applied for all subjects

Thus, comparing these signals we appreciate that we can obtain more robust information from them and, therefore the feature extraction will be better when carrying out the classification afterwards. The first peaks correspond exactly with the rise of the COP in the AP direction before doing the step and it is clear that, in PLS and PCA signals, these peaks are more pronounced. The same happens from the 170th sample (figure 4.4), where the signals represent the ML-COP and every change in the original signal is shown clearer in the new component.

4.4 Classification and Results discussion

Once we used PCA and PLS algorithm for feature extraction, we have the relevant information to classify. This classification is carried out using a support vector machine classifier (SVM).

This method separates a given set of binary labeled training data with a hyperplane that is maximally distant from the two classes (known as the maximal margin hyperplane). The objective is to build a function *(f)* using training data (x,y) [33].

Thus, f will correctly classify new examples (x, y). When no linear separation of the training data is possible, SVMs can work effectively in combination with kernel techniques using the kernel trick, so that the hyperplane defining the SVMs corresponds to a nonlinear decision boundary in the input space that is mapped to a linearised higher dimensional space. In this way the decision function f can be expressed in terms of the support vectors only[33]:

$$f(x) = sign\sum_{i=1}^{N} \alpha_i y_i K(s_i, x)$$

Where K is a kernel function, α is a weight constant derived from the SVM process and the s_i are the support vectors.

In our particular case, the testing was carried out with the 'Leave-One-Out' technique, i.e in every iteration where the training was done, one of the subjects was used for testing. In addition, several Kernels were used in this checking, specifically a linear kernel *('linear')*, a quadratic kernel *('Quadratic')*, a polynomial kernel of order 3 *('polynomial')* and a Gaussian Radial Basis Function kernel*('rbf')* with a scaling factor of 1.

Firstly, we use SVM over PLS data with different components. As we said in the PLS chapter, the rank of latent variables depends on the input data. There is a number of components with which the results are more accurate and the results after the classification are better. Thus, we represent the accuracy, sensitivity and specificity as a function of the number of components and in turn for the different kernel functions. This allows us to determine the best number of components and kernel that we can use.

If we observe the figure 4.5, we can see that, for our data, the *'linear'* and *'polynomial'* functions with seven and two components respectively are the best options to do the classification because the reparation in the space with them allows to classify these data with more precision. In addition, the accuracy is 86.67%, so we can conclude that the classification is precise and optimal and also one possible method to medical diagnostic.

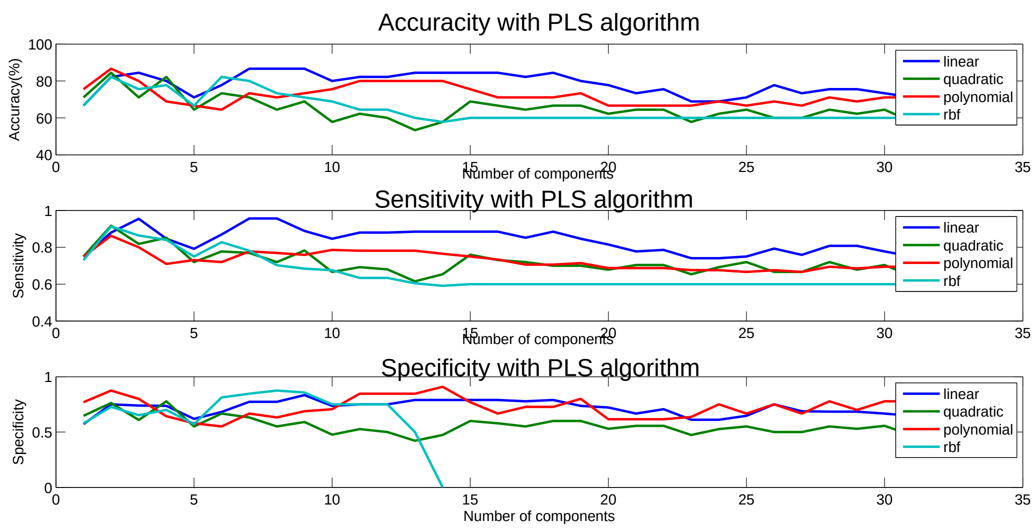

Figure 4.5: Stadistics with PLS data after used SVM to classify.

This can be seen in these 3D representations 4.6 4.7 wherethe points used to the classification as well as the kernel function for the two best cases, i.e *'linear'* and *'polinomial'* functions are shown.

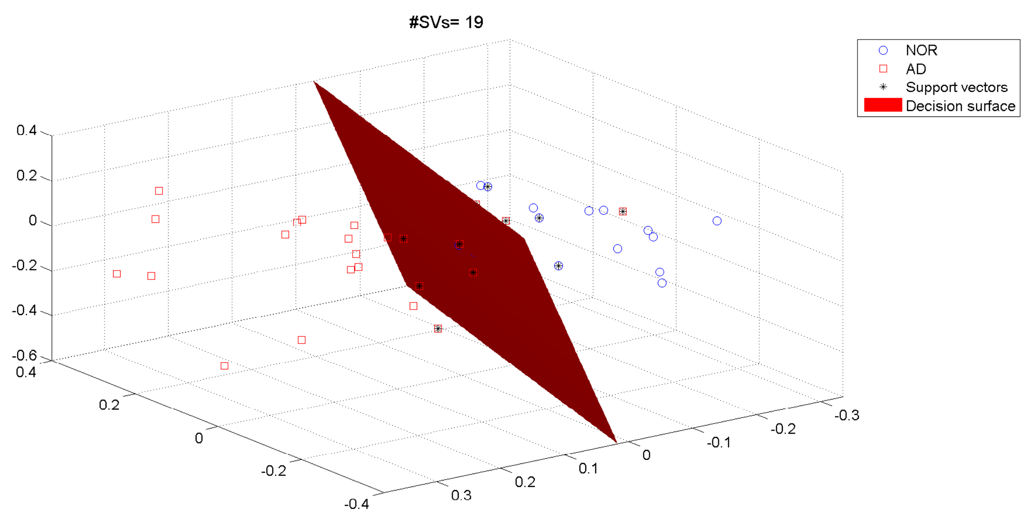

Figure 4.6: Classification of PLS data with the 'linear' kernel.

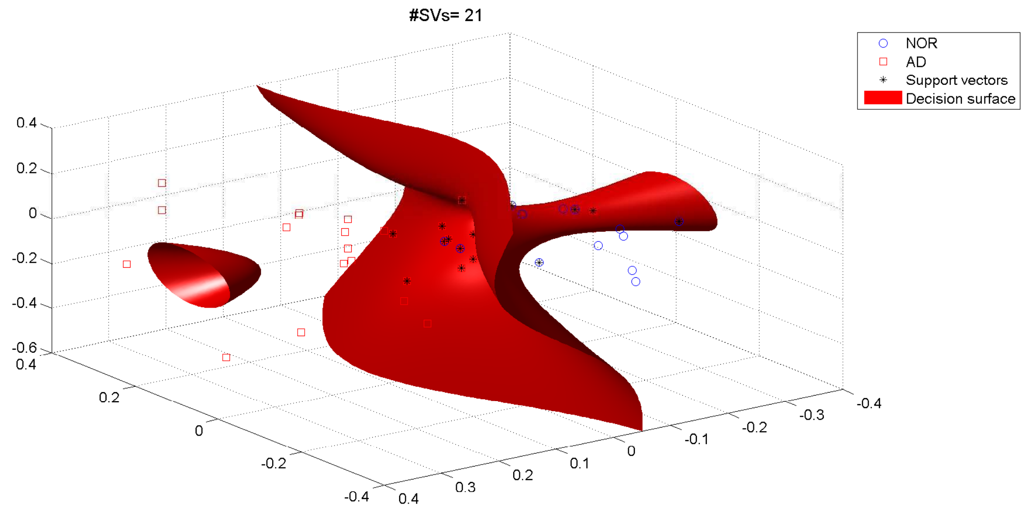

Figure 4.7: Classification of PLS data with the 'polynomial' kernel.

Thereupon, we will do the classification from PCA data. To do this, firstly we select the components that explain most of the variability 4.8.

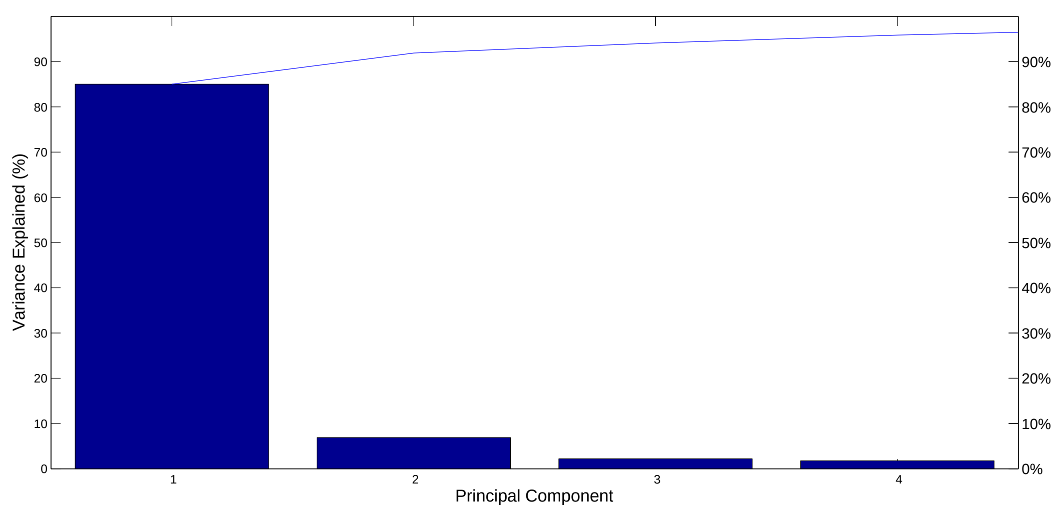

Figure 4.8: Variance explained for PCA algorithm.

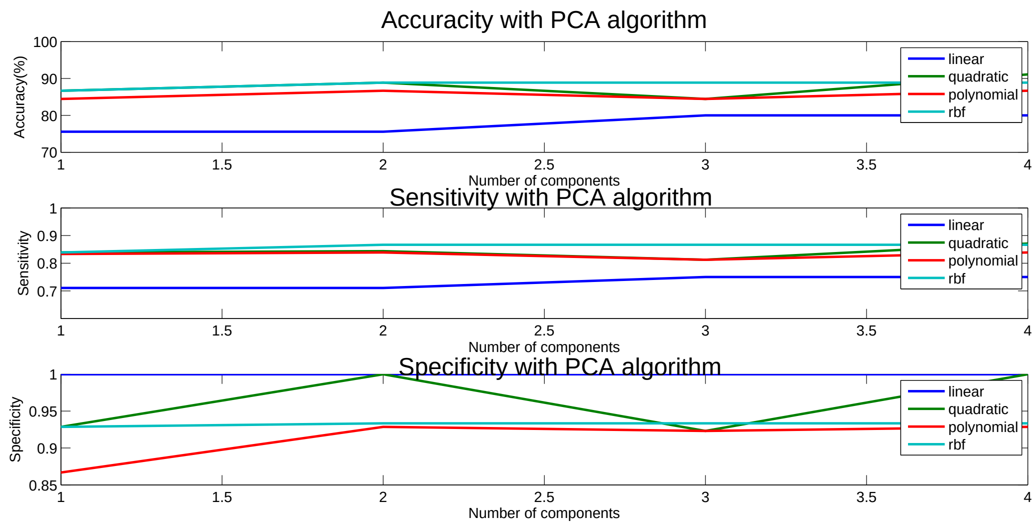

Figure 4.9: Stadistics with PCA data after used SVM to classify.

The screen plot 4.8 only shows the first four (instead of the total forty-five) components that explain 95% of the total variance. The only clear break in the amount of variance accounted for by each component is the first component, explaining about 85% of the variance, so no more components might be needed, and therefore, it is a reasonable way to reduce the dimensions.

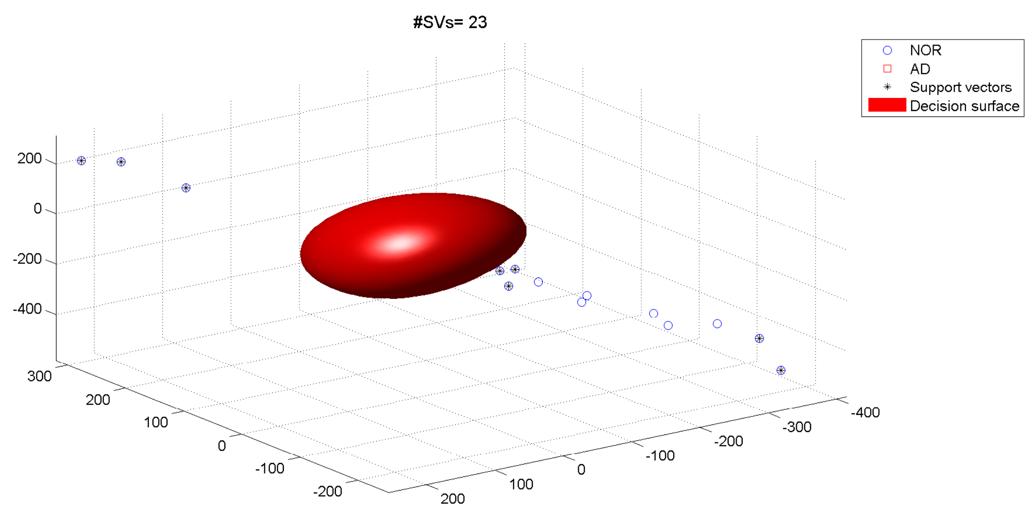

Figure 4.10: Classification of PCA data with the 'rbf' kernel.

Then, we will apply SVM over data for the rank of components between one and four, achieving 91% of accuracy for 'rbf' kernel function4.9. Thus, we can obtain even more precision with this method. It makes sense because the four first components explain the majority of variance.

Also, we can see the result of the classification in the following figure4.10

Finally, we will draw the ROC curve (Receiver Operating Characteristic). It is a graphical plot that illustrates the performance of a binary classifier system as its discrimination threshold is varied. The curve is created by plotting the true positive rate against the false positive rate[45].

The true-positive rate (TPR) is also known as sensitivity. The TPR defines how many correct positive results occur among all positive samples available during the test. In our particular case, it measures how many patients are recognised as such.

The false-positive rate (FPR) is also known as the fall-out and can be calculated as 1 - specificity. It defines how many incorrect positive results occur among all negative samples available during the test, in other words, how many patients are identified as healthy people. The best possible prediction method would yield a point in the upper left corner or coordinate (0,1) of the ROC space, representing 100% sensitivity (no false negatives) and 100% specificity (no false positives). The (0,1) point is also called a *perfect classification*. A completely random guess would give a point along a diagonal line (the so-called line of *no-discrimination*) from the left bottom to the top right corners (regardless of the positive and negative base rates). The diagonal divides the ROC space. Points above the diagonal represent good classification results (better than random), points below the line poor results (worse than random)[45].

The ROC is used to generate a summary statistic. One of the most common and useful measures is *'Area Under Curve'* (AUC) that is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one (assuming 'positive' ranks higher than 'negative'). A rough guide for classifying the accuracy of a diagnostic test is the traditional academic point system[46]:

0.90 - 1 = excellent (A)

0.80 - 0.90 = good (B)

0.70 - 0.80 = fair (C)

0.60 - 0.70 = poor (D)

0.50 - 0.60 = fail (F)

Thus, if we represent the ROC curve using the force data after applying PLS and PCA with a SVM classifier (using a 'linear' kernel), we can see that the ROC curve with PLS is over PCA-ROC curve4.11.

Also, if we calculate the AUC, we obtain that with PLS this value is 0.8344, so the classification is good. However, using PCA data, the AUC has a value of 0.6461, that is to say, it is a poor classification.

In a nutshell, from a accuracy viewpoint, PCA works better than PLS. Nevertheless, PLS is better in terms of sensitivity, obtaining a great difference with regard to PCA as we can appreciate if we compare the AUC values. Thus, we can conclude that, in general terms, PLS could give us better results because the difference in accuracy is less than the difference in ROC analysis.

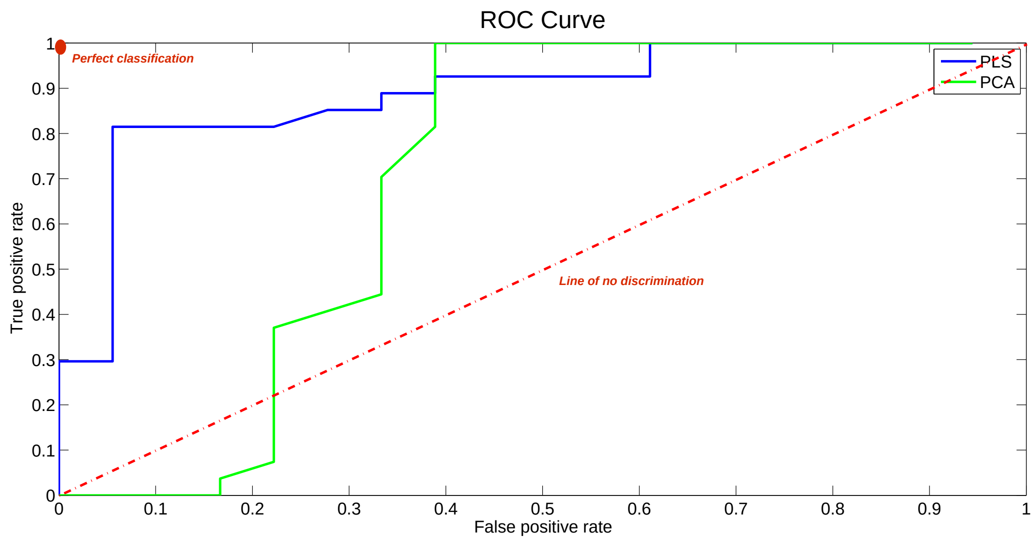

Figure 4.11: ROC Curve for PLS and PCA with SVM classifier.

Chapter 5

Gait Watch and Qualisys Optica motion tracker

5.1 Introduction and chapter's structure

After explaining and comparing both Gait Watch and Force Plate systems, we proceed now to do an analysis of the differences and similarities between Gait Watch and the Qualisys Optical motion tracker.

It has been demonstrated that Qualisys System is an accurate system to analyse the body movements and it can be used in several applications. However, this system has a lot of constraints like the possibility of application scope.

Thus, we are going to do a comparison with the Gait Watch system, a system based on inertial sensors being more portable and cheaper. Along this chapter we will explain how the pitch angle has been calculated using the Qualisys System. That is, we will compare with the angles obtained through inertial sensors.

5.2 Computing Euler angles using Qualisys System

To compute the Euler angle, the subject is wearing two infrared markers per segment placed on both thighs and shanks. The infrared optical cameras emit infrared light and this reflects in the markers placed over the body allowing to know the position of the markers.

The pitch angle of such segment is computed between the vector defined by the upper and lower markers and the vector normal to the Earth's surface. To be able to compute it we first have to define a third point which has the same X coordinate as the lower marker and the same Z coordinate as the upper marker. This will define a right triangle in which one of the contiguous cathetus is normal to the Earth's surface and the hypotenuse is defined by the line between the upper and the lower point. Therefore, by calculating the arctangent we can easily find the angle of the right triangle, which is, in turn, the pitch angle[4]. We can see this in 5.1

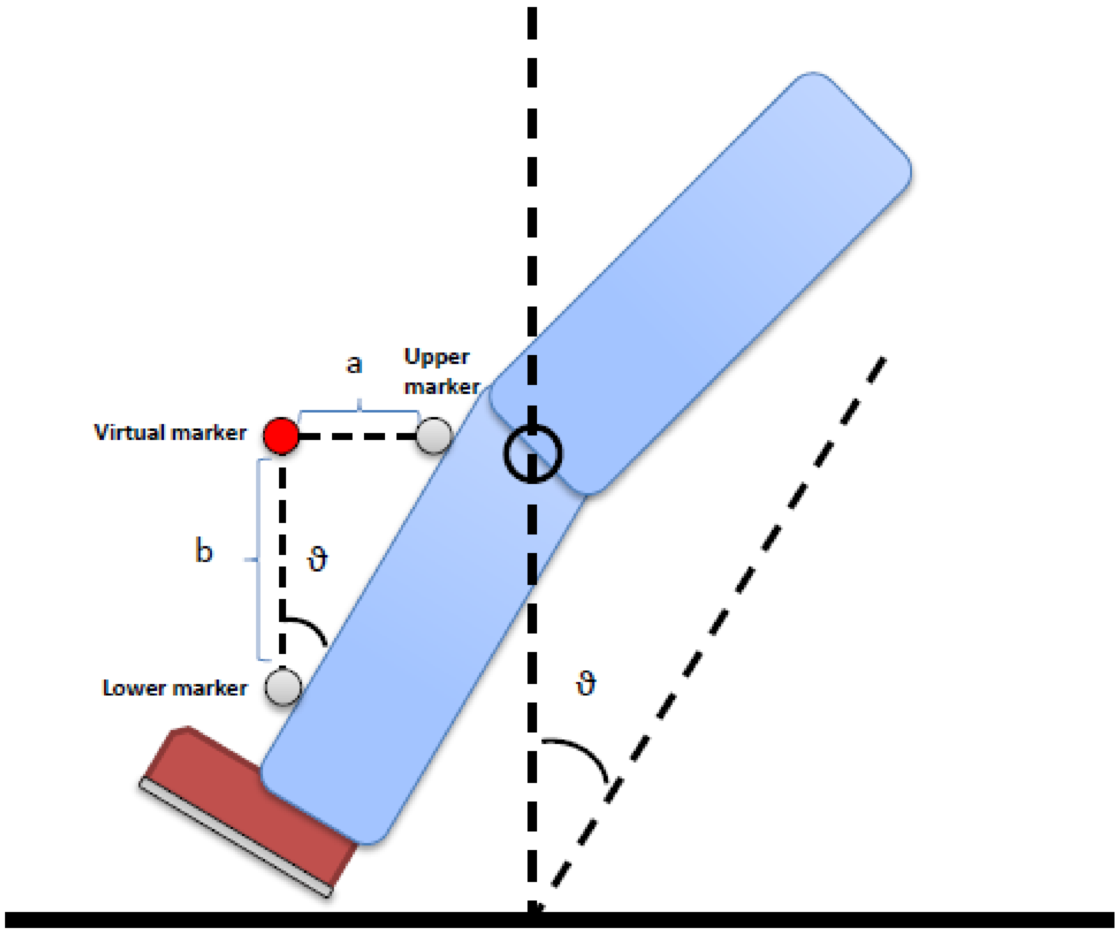

Figure 5.1: Diagram of the pitch computation using the Qualisys System [4].

Thus, the pitch angle is computed as follows:

$$\theta_{QS} = arctang(\frac{a}{b}) \tag{5.1}$$

$$a = \sqrt{(x_{upper} - x_{lower})^2 + (z_{upper} - z_{upper})^2} \tag{5.2}$$

$$b = \sqrt{(x_{lower} - x_{lower})^2 + (z_{lower} - z_{upper})^2} \tag{5.3}$$

where $[x_{lower}, z_{lower}]$ and $[x_{upper}, z_{upper}]$ are the coordinates of the projections of the lower an upper markers in the XZ plane, respectively.

5.3 Feature extraction

In this experiment, prior to start the data gathering, we set up the protocol that people have to carry out while the data are recorded. Seven control subjects have been involved. They had to walk during some minutes over a treadmill with different speeds, specifically 2, 4 and 6 Km/h.

This movement is characterised by the Gait Watch system and the Qualisys System. To do this, the participants wear the inertial sensors over the body and the infrared markers, being these last ones visible by infrared cameras all the time. This experiment is carried out in a control environment where both systems can work properly.

Once the data have been gathered, we process them before the applying the feature extraction. For the GW signals, the procedure is the same than in aforementioned cases. The first step is doing the calibration and correct the erroneous values in the signals due to a noise of the sensors. Then, we can figure out the angle of the different segments of the body. The program done in Matlab allows us to choose what segments we can use to calculate and compare between both systems. In this case, we can select: right shank, left shank, right thigh and left thigh.

The angle of these segments are calculated for each point of time with a sample frequency of 200 samples/s for both systems so we do not have to interpolate because these signals match perfectly. The pitch is filtered with a Kalman Filter in the GW signals because it is an algorithm that uses measurements observed over the time and produces estimates of unknown variables that tend to be more precise than others based on a single measurement. In other words, Kalman Filter operates recursively on a stream of noisy inputs data to produce a statistically optimal state of the underlying system state[**?**].

Hereafter, we calculate the pitch using the QS signals. To do this, we will apply the equations described in the previous chapter 5.1. After this, we have to center all of these signals and we will be ready to compare all signals now.

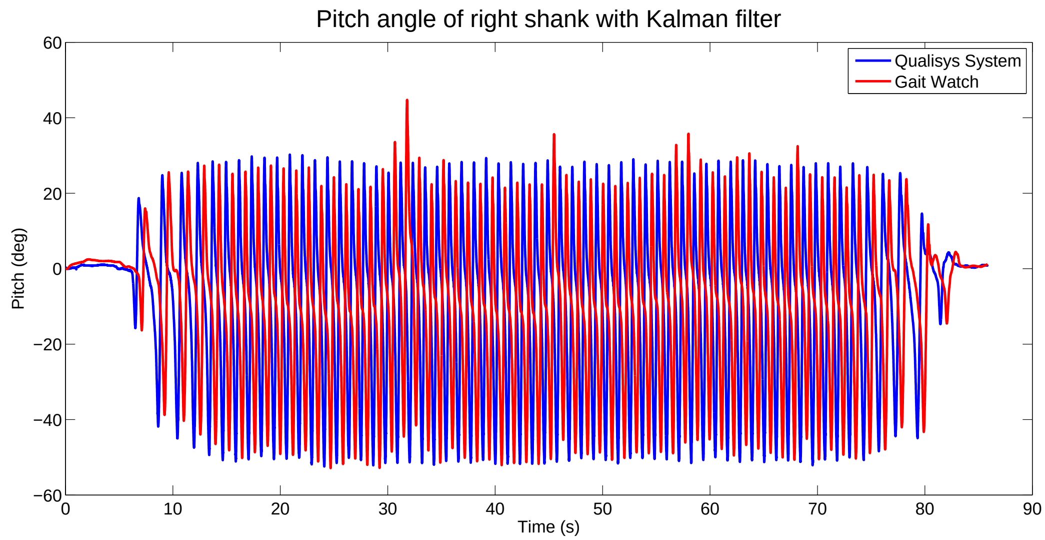

Figure 5.2: Pitch angle of right shank for 4Km/h of speed.

The next step is the feature extraction. We have to differentiate two comparisons. Firstly, we are going to compare the pitch calculated with inertial sensors (GW) and infrared cameras (QS), so we will extract some specific characteristics to do this. After that, we are going to compare the angle obtained in function of the speed with which the subjects walk on the treadmill.

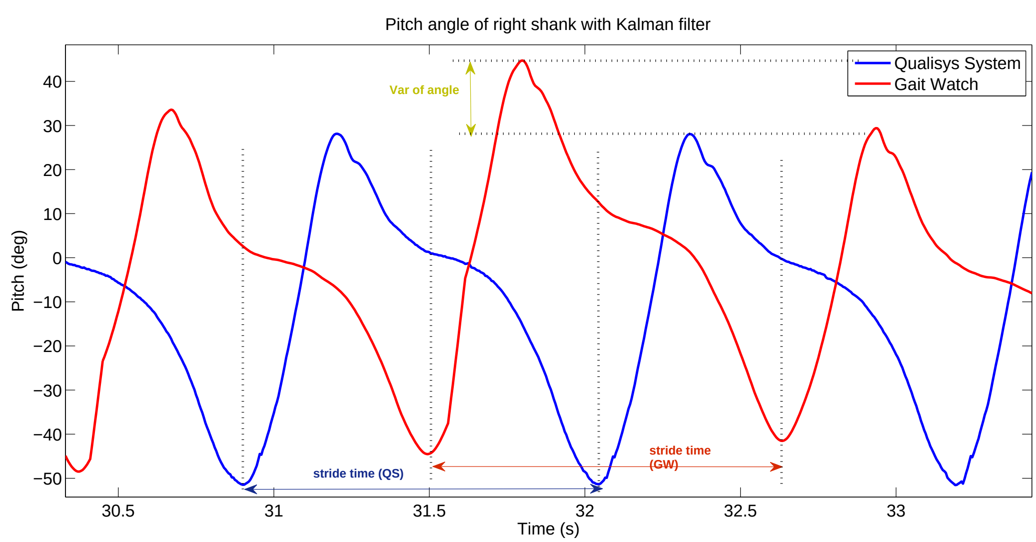

Figure 5.3: Features for pitch angle in GW and QS signals.

The first feature computed was the ‘stride time’ 5.3. This is the time that a person needs to carry out a step, i.e the time since the foot is lifted from the treadmill until the moment when the same foot touches the ground and gains momentum to step again. In the pitch signal, we determine this by detecting the distance between two negative values of the pitch because the negative values happen when the segment (shank or thigh) are behind the trunk, this is just before stepping.

Other important aspect is the difference of angle obtained in both systems. We calculate values positives as well as negatives and finally obtain the mean of the difference of all them 5.3.

5.4 Results discussion

Once the features have been calculated, we proceeded with the comparison between them. Firstly we can see the differences between 'stride time' in GW and QS signals in 5.4. This figure shows the differences between them are minor so we would use the GW in place of QS with regard to this variable.

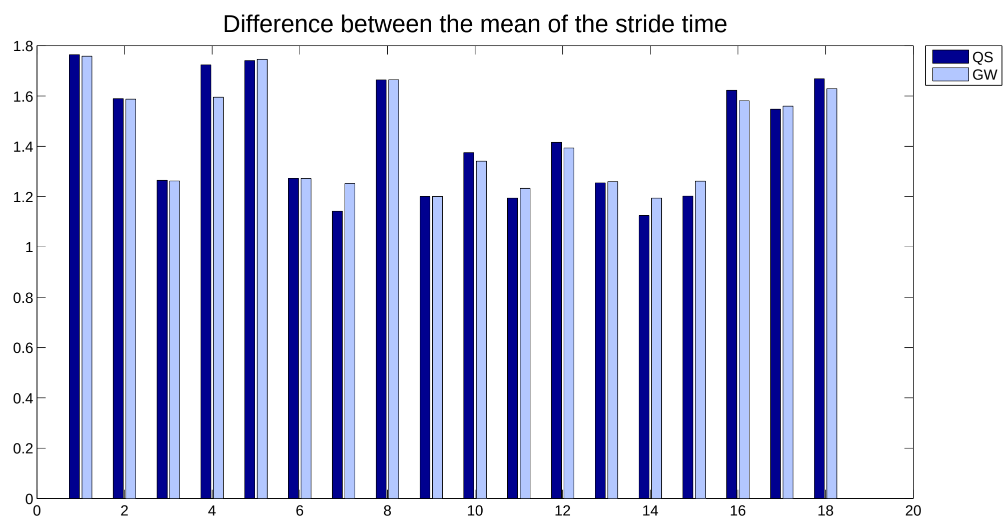

Figure 5.4: Mean of the stride time for GW and QS signals.

'Stride time' is a feature used in a lot of experiments to characterise the movement because it is an interesting aspect that represents the time that a specific person needs to step. Also, it can be used for a classification between patients and control subjects, like in others studies [47]. In our case, the difference between the 'stride time' between both systems is very small. If we observe 5.1, we can see that the greatest value of difference between systems is 0.1287 seconds.

In addition, it has been obtained the variations between the mean of the variance of the

Table 5.1: Comparison of the stride time and angle difference between GW and QS

Accomplishments	Difference Stride Time	Difference Angle
1	0,006402343	1,62502323
2	0,00214919	2,119358046
3	0,002432735	3,166649918
4	0,128717949	1,983148998
5	0,004818214	2,418373859
6	0,000302102	2,884211822
7	0,109688664	2,000748905
8	0,000282755	2,606004581
9	0,000604613	0,644265922
10	0,034118318	2,093221696
11	0,038589012	2,597329501
12	0,022069119	0,039397798
13	0,004924869	2,771227548
14	0,069355008	2,87790541
15	0,059470686	2,227618016
16	0,041612352	0,511020994
17	0,012348426	1,834745133
18	0,039846301	1,701994772

Table 5.2: Features for different speeds

Speed	Stride time Diff Average	Stride time var Average	Angle Diff Average
2	1,6894	0,00086	2,36
4	1,2397	0,017	4,1521
6	1,4479	0,0094	4,6219

'stride time'. This parameter gives us information about the accuracy of both systems to calculate the pitch angle during the experiment.

In the majority of the accomplishments of the experiments, the variance of the GW system is greater than QS 5.5. It is probably due to the noise of the inertial sensors and the accuracy to calculate the pitch. However, they are very low values so it is not an important aspect that determines the quality against each other.

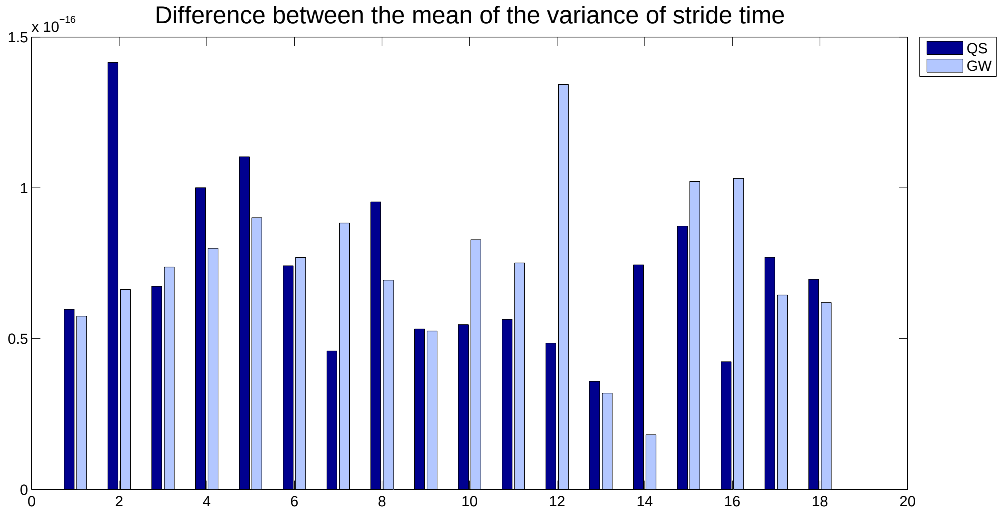

Figure 5.5: Mean of the stride time variance for GW and QS signals.

Now, we will compare the mean of the angle in each experiment. The result of this is depicted in 5.6. It is clear that the differences are not large. The greatest value of difference between angles is 3.16 degrees5.1. If we calculate the percentage with respect to the total average, this is about 12% of the angle. This precision might be important depending on the application. In general, it is not a significant value to characterise the movement. Therefore, Gait Watch system may be used to substitute the Qualisys systems as a good alternative regarding the accuracy, price and portability.

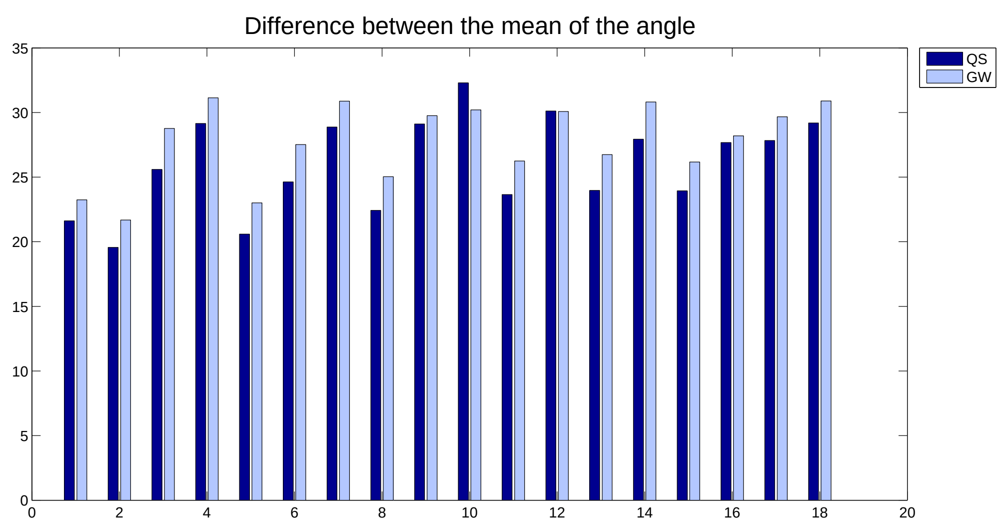

Figure 5.6: Mean of the angle for GW and QS signals.

Then, we will see what happens when we analyse the signals with regard to different speeds. In 5.7, we can see the mean of stride time for speeds of 2, 4 and 6 Km/h. If we have a look at the points represented in the picture, it seems that the 'stride time' is greater for low speeds than high speeds although it depends on the subject. In 5.2 it is shown the mean of all values for each velocity. The average 'stride time' is higer for 6Km/h than 4Km/h. However it does not happen in general. Therefore, we would need more measurements to establish a final conclusion.

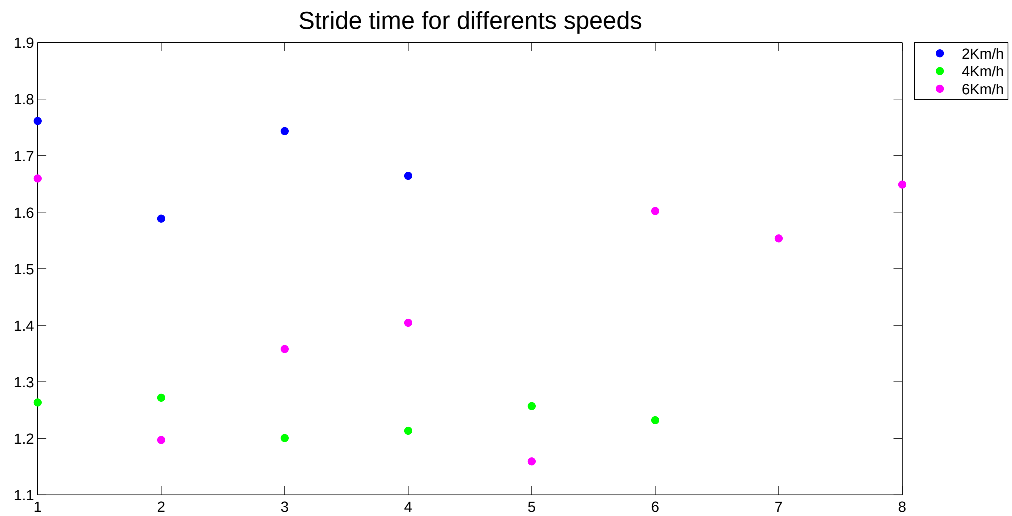

Figure 5.7: Mean of stride time difference for each speeds.

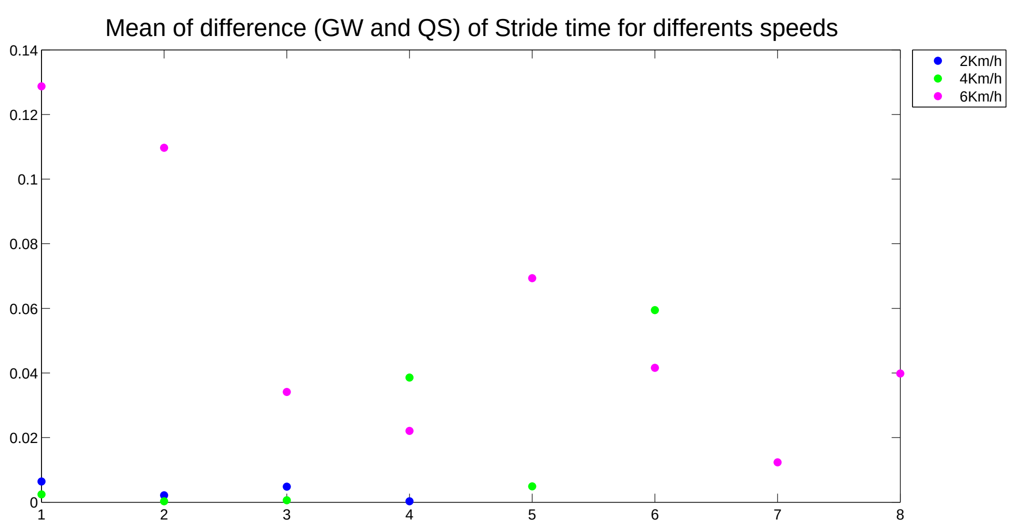

Figure 5.8: Mean of stride time variance for each speeds.

If we scan 5.8, we can appreciate the differences between the variance of 'stride time'. Also, the mean of the values for each speed are put in the table 5.2 and the variance increases as the speed does it as well.

It is the same with the difference of the angle between systems 5.9. The difference between angles increases with speed. So, it is an aspect that we have to consider to use the GW in place of QS.

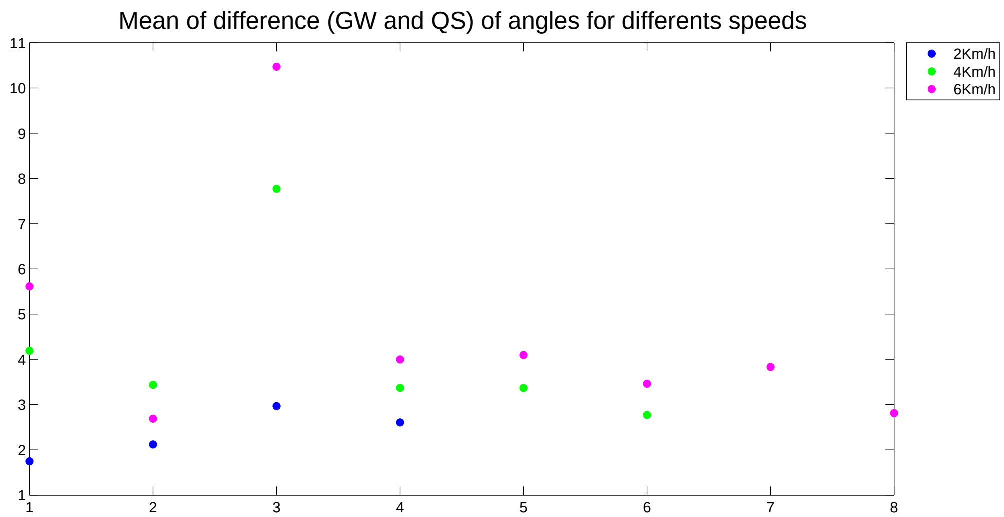

Figure 5.9: Mean of angle difference for each speeds.

Chapter 6

Potential Applications

After doing a study about the different systems to monitor and analyse the postural adjustments, we proceed to explain possible applications in real life.

The force plate system is a very accurate system to analyse disorders in the patients, however it is a limited system for its price and portability. So, its applications may be restricted to diagnosis of some diseases. The same happens with Qualisys System because of the need of fixed cameras to record data. However it is a interesting way to observe data in real time with precision and robustness.

But, without a doubt, the Gait Watch System is one of the most interesting systems due to its portability and its amount of fields where it can be used such as telerehabilitation, analysis of daily activities and performance of some athletics. This is why, the majority of applications will be focused in this system.

All of these implementations will be briefly explained below as well as a business idea as a concrete application of this project.

6.1 Diseases

There exists a large amount of diseases that distort the motor control of human body or present symptoms that can be identified by the analysis of human body posture and motion. Along this section, we will briefly comment how our study has influence in that.

6.1.1 Neurological and Muscular diseases

Parkinson's disease is the second most frequent neurodegenerative disorder after Alzheimer[48]. According to the Parkinson's Disease Foundation, PD is a chronic and progressive movement disorder, meaning that symptoms continue and worsen over time[5]. Many as one million Americans and 60,000 Spaniards and 10 million people worldwide live with Parkinson's disease. Also, there is a large number of cases that go undetected [7].

Primary motor signs of Parkinson's disease include tremor, bradykinesia, dyskinesia and disorders in the posture and gait. Bradykinesia is the term for defining slow execution of the movement, tremor is the term used to define repetitive periodic movements within a certain frequency range and dyskinesia is a movement disorder which consists of effects including diminished voluntary movements and the presence of involuntary movements. Inertial Systems could be used to detect these disorder and help to diagnose and monitor them [7].

Another disease associated to the central nervous system is **Multiple Sclerosis (MS)**. MS is an autoinmune disease characterise by scar tissue resulting from the repair of damage to the myelin sheath that surronunds neurons. MS affects approximately 2.5 million people worlswide. Symptoms of MS are unpredictable but may inlcude fatigue, visin problems, loss of balance and coordination, or depression. Also, individuals with MS often have poor balance control that is especially apparent during dynamic task such as gait initiation. Hence, Inertial Sensors may be a useful tool to detect these symptoms [26].

Cerebral palsy (CP) is important to be mention because it is a movement disorder appears in early childhood. CP is a neurodevelopmental condition caused by non-progressive brain lesion, can occur before, during or shortly after birth. Children diagnosed with CP demonstrated increased muscle activity to sustain posture, agonist/antagonist co-contraction, impair postural control, inadequate force production, and restrictive voluntary ans selective control of movement[2].

These impairments not only interfere with performance of functional activities, but also with opportunities and/or willingness to participate in leisure, community ans school activities.

Impaired postural control in CP includes difficulty organizing compensatory postural adjustments (CPAs) and anticipatory postural adjustments (APAs) [2]. For that purpose, consideration should be given to the use of Inertial Sensors to monitor this disease in daily life.

6.1.2 Sleep disorders

Sleep disorders cause an unrestful sleep and important repercussions in some cases such as sleepiness and psychiatric and cardiorespiratory secondary disorders[49].

In order to diagnose them, we can use inertial sensors to monitor changes that occur during sleep. In addition, it is a good option to do this in a cheap and portable way, so that patients can move freely while they are being monitored[7].

Also, the information gathered can provide information of the cardiac, respiratory, and snoring activities of patients sleeping[49].

If we use all of this at home, it is possible to provide a tool to sleep specialists for knowing the behaviour of the patient when they are sleeping, what sleep cycles are more affected and improve their medical treatments.

For example, some of the patients with **Epilepsy** suffer as tonic-clonic nocturnal seizures. These seizures may go unnoticed to the patient, thus, during the control sessions with the doctor the patient could not tell the doctor these episodes. To avoid such a situation, the patient may sleep with an attached MIMU so nocturnal seizures can be detected and stored in the memory, allowing the doctor to notice that nocturnal attacks are happening[7].

6.2 Daily activities

Providing new wearable technology for medical and surgical **rehabilitation** services is emerging as an important option for clinicians and patients. Wearable technology like inertial sensors provides a convenient platform to be able to quantify the long-term context and physiological response for individuals[50].

In the first phase of the rehabilitation program the patient have to move to the medical center for treatment. However, the second phase patient have to do low intensity exercises to strengthen the muscles. This last task does not require continuous supervision, thus, MARG systems can avoid the overcrowding of rehabilitation centers and patient can do the exercise at home comfortably[7].

In addition, doctors can then supervise the sessions carried out by the patients by remotely checking the logs. Also, they could detect different activity states, for example, knowing whether a person is sleeping, driving or doing exercise[7].

Fall detection is an important aspect during daily life of elderly people. It is very clear that falls are a serious health issue and that systems automatically detecting a fall and calling could be of great help to solve it.

Moreover, there are applications for the motion analysis in **sport activities** by attaching sensors like accelerometers and gyroscopes onto the athletes' body segments. For example, for a swimmer, the discrimination of the swimming styles and the segmentation of the underwater stroke phases could be achieved. In addition, the physiological response was also detected on the wrist acceleration when the swimmer was fatigued in analysis method the intensive training situation[51].

6.3 Business plan

6.3.1 Executive Summary

SmartManagement claims to improve the quality of life of elderly people and with motion disorders. This system can detect falls and call emergency ambulance service as well as gathering data from the inertial sensors to analyse the postural adjustment and the different movements and activities during the day. This information will be sent to a server, so the doctor can access this information doing a medical monitoring of the patient and changing the treatment whether it is necessary.

To do this, we will use inertial sensors attached over legs, trunk and arms. This devices are more wearable and cheaper than other systems for gait analysis. This lets us making a cheap and comfortable design for our customers. The signal processing will be carried out by an application in android that will communicate with the devices. At the same time, this application will transmit this information to the server.

The Gait analysis with inertial sensor is an innovative field specially in Spain where there are not companies in the market developing this kind of products. Population get older and their necessities grow being their monitoring and self-reliance increasingly important. There are international companies such as 'Gaitup' whose main goal is to perform assessment of the gait and fall detection. This is an important competence but firstly we will focus on the domestic market and also we will provide improvements in price, communication and services.

To achieve that, we will contact with hospitals and old people's homes as well as with public institutions because we plan that users only pay a portion of the cost of the product. Also, we want to find private investors providing them publicity in return for a investment.

We plan to establish presence in Internet and social networks to show our product. With this, people will be able to know what we do and how can improve their lives, those of their relatives and other loved ones.

We can see a visual summary of this using a Model Canvas [Second appendix].

6.3.2 Company Description

SmartManagement is a technological-based company whose objective is the implementation and development of completed system to monitor elderly people with motion disorders. The company is currently developing a research work and seeking to establish its corporate identity in the medical product field.

Our method for developing businesses is the 'lean starup', so the product is not closed, but we receive information from our customers to improve the prototype and provide their requirements.

The main motivations why this Project will have an impact are:

- As population age, health expenditures tend to grow rapidly since older persons usually require more health care in general and more specialized services to deal with their more complex pathologies (Statistics from DESA, World Population Ageing 2013[52]).

- Globally, 40 per cent of older persons aged 60 years or over live independently. This indicate the necessity of continuous assistance (Statistics from DESA, World Population Ageing 2013[52]).

- One of the largest cause of disability and health problems in old age are falls and immobility (Stadistics from DESA, World Population Ageing 2013[52]).

- For the elderly who fall and are unable to get up on their own, the period of time spent immobile often affects their health outcome. Muscle cell breakdown starts to occur within 30-60 minutes of compression due to falling. Dehydration, pressure sores, hypothermia, and pneumonia are other complication that may result[7].

The objectives of the company are as follows:

- Improving the quality of life for elderly people.

- Making a Custom-made design so it will be different and fit for each people.

- Avoiding the overcrowding of old people's home and hospitals.

- Increasing the length of home stay where old people used to be more comfortable.

- Helping elderly people as well as people with motion disorders, increasing their self-reliance.

- Establish a medical advisory board.

6.3.3 Market Analysis

Over the past few decades the increased level of public awareness concerning healthcare, physical activities, safety and environmental sensing has created an emerging need for smart sensor technologies and monitoring devices able to sense, classify, and provide feedbacks to users' health status and physical activities, as well as to evaluate environmental and safety conditions. This makes the project more interesting and specially timely.

The potential customers of SmartManagement are both domestic and foreign although we will focus in the first segment.

Domestic customers include hospitals, elderly people and people with motion disorders like Parkinson Disease or Cerebral Palsy. Also, we have to considers the key partners like public institutions, suppliers or Universities where there is a great research in this field. The foreign market includes many of the above segments but also includes key partners such as inertial sensors distributor.

This kind of products are not marketed in Spain. However, there are some institutions and companies working in similar investigations. Telefonica together with UPC (Polytechnic University of Cataluña) had developed a inertial sensors-based system for monitoring Parkinson's motor symptoms[53].

In the international market, there are several companies developing products for gait analysis and activity monitoring. The main competitor is a Swiss company called 'Gaitup'[54]. This comany was founded in 2013 with the will to make products and solution for evaluating health and performance, based on wearable sensor technology.

Gaitup develops products like 'Gait Analysis' whose goals are evaluation of the treatment, fall risk and motor symptoms assessment and feedback to the patient. Also, 'Activity monotoring package' allows the identification from long-term data, healthy status and evaluation in home environment.

However, **SmartManagement** is not only focused in the product, but also it seeks the comfort and the necessities of the customers. Thus, custom-made designs and adapted to economic status of our customers will be produced. Also, another added value is the realization of courses to teach the operation and advantages of the product.

Intel and Michael L.Fox Foundation are working in wearable technology for Parkinson disease. They announced the development of sensor technology and analytics platform for Parkinson's treatments and monitoring[1]. Although it is focused in Parkinson disease, it could be expanded to other diseases or fields. Also, this indicates the importance of this type of project and its social impact.

6.3.4 Organization and Management

SmartManagement will have a CEO, who will be in charge of managing. Also, the company will have the next structure:

- **Hardware Department**: this department is in charge of the design of the devices, i.e the types of sensors, their structure and position and market study of inertial sensors and new trends.

- **Software Department**: this department is divided in two more. One of them will be in charge of the signal processing and data analysis. The second one will carry out the mobile application to gather and process the data in real time and send an urgent message whether this is necessary (for example, a fall).

- **Communications and servers Department**: data will be processed and sent to a Server so the doctor is able to obtain the results for adjusting the treatment.

- **Marketing Department**: all information about the project will be shown in social networks. We consider the activity in social networks is very important and one way to show the importance of this project and its possibilities. In addition, we will make a Web Site that will be used to contact us and show our products and services.

- **Administration Department**: this department will be in charge of the administrative topics such as possible investors, legal issues and economics tasks.

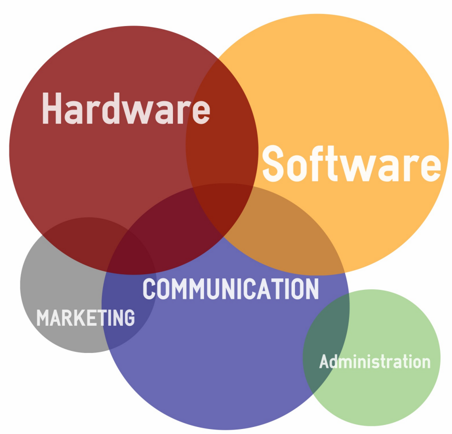

Figure 6.1: Diagram with the different departments in the company.

6.3.5 Product Line

The following is a brief explanation of the production process:

- Assembling and configuration of inertial sensors. To do that, first we will obtain MEMs from ACAL bfi. Although there are a lot of supplier can provide these devices, we finally choose this one because it offers a great variability and quality in its products.

- The next step is to use the signals from inertial sensors to carry out the signals processing and extract the main information to characterise the gait and others aspects such as falls or problems in the movement.

- At the same time, we initially will do an application for Android smartphones and when this works properly, we would like to expand to iphone as well. The final idea is that everybody can use our product.

- Then, we have to control the communication between inertial sensors and Smartphone as well as the communication between the mobile phone and cloud. We have to differentiate between the normal data transfer and urgent call. In the first one, the data transfer between the Smartphone and cloud will send information to the server for afterwards the doctor can use this information and adjust the treatment of the patient. In the second one, the process is different because the mobile phone calls automatically to emergency department when a person is at risk of falling or other similar situations.

- Once we have a first prototype we will apply the 'lean startup' method. Some companies begin with an idea for a product that they think people want and after long time the company realises that customers do not like the product. For this reason, we want to establish a feedback with our customers before setting the final product, so business will grow with maximum acceleration.

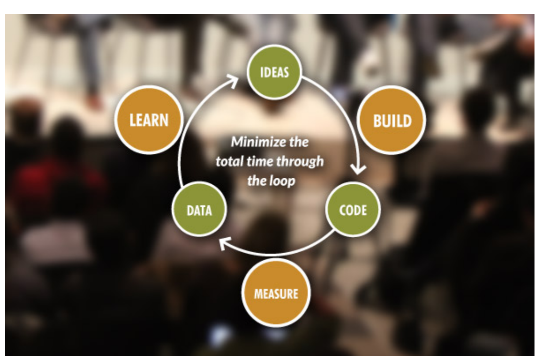

Figure 6.2: Process of the 'lean startup' method.

6.3.6 Marketing and Sales

We will leverage a marketing and sales campaign because we are aware of firsts sales will be possible with a strong presence in social networks. The marketing strategy will have two phases. The first one is as follow:

- Publicity in Internet. We will advertise on our Web Site and we also plan to invest in Google Ads for reaching people.

- Building of Web Site. We will create a Web Site where we will show the description of our product and its possibilities to improve the quality of life for elderly people. Also, our customers will be able to buy the products here or contact us.

- Publicity off-line. It will be carried out using informative meetings to show the advantages of this project. In addition, we will visit hospitals and old people's homes to inform about it personally.

- Marketing on-line. Social network such as 'twitter' and 'Facebook' are useful tools to advertise our products. Also, we want not only to show our advances but also keeping them actives publishing regularly. We will use 'linkedin' for providing employment and building a network outside contacts. In addition, we will create a blog to give suggestions to elderly people with motion disorders because we want to transmit our social engagement as well.

- Presence in conferences, trade fairs and exhibitions.

Regarding sales strategy, these will sell on-line on the WebSite. However, we are aware that most of elderly people do not use technologies, so we will use the hospitals and old people's home to distribute the product. Also, we could send the product to their homes directly whether it is necessary.

6.3.7 Finaltial projections

Smart Management will be funded by an initial investment from the stockholders of the company and public institutions. It is important to develop awareness of the importance of this fact and obtaining grants to make the product.

We will need public grants because we consider that elderly people should not pay a lot for these devices, so a part of the price will be funded by foundations and government and another by the user.

In addition, we are going to look for investors for the project. They will be able to receive publicity and partners from our company. Thus, other goal for the company is to create a good relationship between partners and investors.

An amount of money achieved will be for hardware, software licenses, accommodation and marketing. The rest of the money will set aside for salaries of our employees. At the beginning the salary of the stockholders will depend on the company economy. After two or three years this will be adjusted, so they will have a fixed wage.

6.3.8 SWOT Analysis

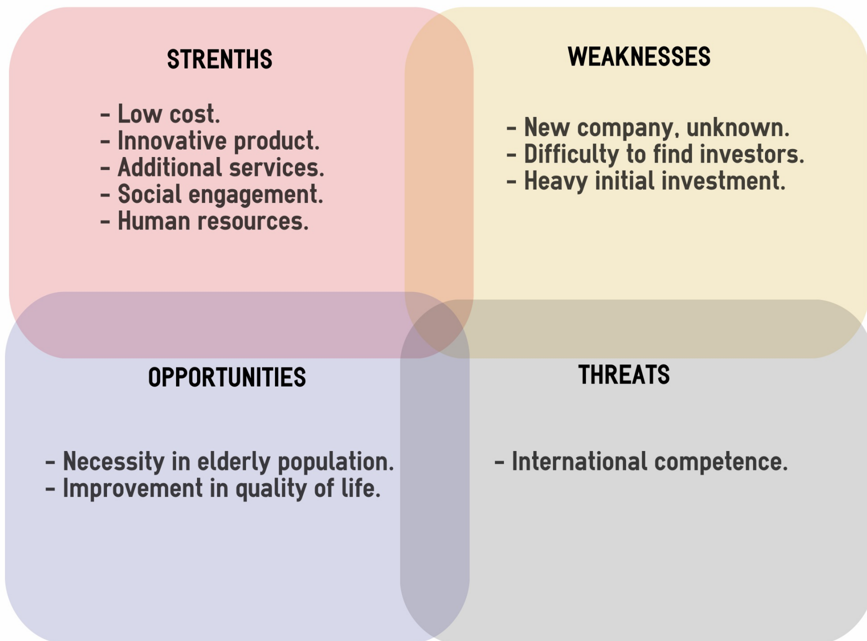

Figure 6.3: Table of the SWOT Analysis.

Chapter 7

Conclusions and Future Work

7.1 Conclusion

The analysis of posture and human body motion has gained special relevance within the past years in many medicine fields, as well as in others kinds of applications. Traditionally, this analysis has been carried out by Force Plates and systems base on cameras of high speed using infrared markers. This fact has restricted the fields of applications due to the price, portability and limitations of visibility. For this reason, we have carried out a comparative study of these systems in contrast with low cost devices based on magnetic and inertial MEMS microsensors (Gait Watch).

To do that, we have applied different techniques and procedures that we have explained and compared along the project. In addition, our work has a direct application, not only in diagnosis of Parkinson's disease, but also in neurological and muscular diseases such as Multiple Sclerosis, Cerebral Palsy and Epilepsy. In the application field, we focus on the analysis of posturographic Body-sway to detect disorders in Parkinson patients as well as falls in elderly people which are becoming increasingly frequent.

Finally, we proceed to analyze the initial objectives that were enumerated in the introductory chapter to determine to what degree they have been fulfilled.

- **Synchronisation**

  - One of the objectives in this section is to carry out the synchronisation between FP and GW signals. We have several signals from both systems: force, AP-COP, ML-COP, etc. in the FP system and acceleration, angular velocity, pitch, roll, etc. in the GW system, having both systems a different sample frequency. Thus, the procedure is: choose the appropriate signals to do the synchronisation, detect a common point between them and interpolate them. After a deep analysis of these signals, we concluded that the best signal to do the synchronisation is the acceleration of the shanks and the force over the platform because you can detect in both signals when the patient touches the platform and finally do a appropriate matching. In addition, we compare the synchronisation done with the acceleration and angular velocity of the shanks obtaining a similar result that indicates this a good procedure to do the synchronisation.

- Other goal emerged during the development of the project is the comparison between FSD (Framed Spectrum Detector) and LTSD (Long Term Spectral Detector) algorithm to determine the intensity motion. We determined after doing the comparison that LTSD is a better method for our signals because it is designed to work under condition where the SNR is low, i.e the signal presents large noise. In our case, we want to detect the different cycles in the GW signals that correspond to each repetition so the different peaks of activity inside each period can be a problem to do the detection correctly because they are interpreted as noise by the detector. Thus, the LTSD method is more interesting for this type of signal.

- **APA analysis**

  - One of the main goals of this project is to analyse the APAs and determine whether there is a pattern that allows us to characterise the movement before gait. The signals used for this were the acceleration and angular velocity of the trunk and the center of pressure obtained from the force measures of the force plate. The conclusion is that we can see a pattern in all these signals and also it can be detected when the patient starts to step with the right or left foot. This is a great advance because we can obtain information and extract features of these signals.

  - Analysing the state of the art we can find that there are several articles that show what and how the features are extracted. Typically, the features more used to characterise this kind of movement are the peak of acceleration and COP. We used these features as well as other peaks in these signals that we considered that could be interesting. Also, we calculated the duration of the APA in COP, acceleration signals and gyroscope signals.

  - We focus on the PCA method to extract features because it allows us the reduction of redundant information and the interpretation of multiple gait signals. We extract the same features mentioned above before and after applying PCA. We conclude that the acceleration and angular velocity can be substituted by only one of them because there is not variance between them. This is an important conclusion when we have a big data base. Also, we used PCA between patients, being this the first step to do a classification in a future work.

  - If we focus in chapter3, we can determine that there is a significant correlation of some of the features calculated between FP and GW signals. Although we should expand the data base before drawing a definitive conclusion, we could say it is possible that devices based on inertial sensors can replace platforms. This would allow to do a lot of different experiments without limitations of space and price.

- **Classification of force data**

  One of the main goals in this experiment is to determine whether it is possible to classify Parkinson patients and healthy subjects from force data. We tested two different methods to extract features: PCA (unsupervised) and PLS (supervised) using SVM as classifier. The conclusion of this is: firstly, PCA is more appropriate from an accuracy viewpoint and PLS has better results than PCA from a sensitivity viewpoint, secondly we can obtain a good classification with both methods. This allows us to conclude that the analysis could be used to help in the diagnostic of Parkinson's disease.

- **Qualisys system and Gait Watch (treadmill experiment)**

  - An initial objective was to determine what kinds of features we could extract in this type of experiment. The signals used to analyse this behaviour are the pitch angle of shanks and thighs. Thus, we concluded that the most interesting aspects to consider were 'stride time', variance of 'stride time' and peaks of angles. 'Stride time' has been a feature used with success in other similar studies so we though that it could be a significant parameter.

  - Determining the accuracy of the pitch angle obtained with GW and QS systems was another of our targets. To do this, we compare the features calculated from the pitch. The conclusion is that we can use the GW in place of QS in the majority of the cases if we need accuracy in the angle and 'stride time' because the difference of both is minimal.

  - In addition, we compare both systems in different conditions of speed to determine if the velocity affects in the accuracy of the systems. After the study, we can say that speed influences in the variance of 'stride time' and angle, i.e when the speed is higher the difference between systems to calculate the 'stride time' and angle increases.

7.2 Future Work

As we have done for the final conclusions, we proceed to analyze future work for the two main parts of our system.

- **Force Plate and Gait Watch (experiment with Parkinson patients over a platform)**

  - We will increase the data base of the patient for achieving results more accurately. Currently, we have a limited data base with only five patients. This gives us a rough guidance of the information that we can obtain but it is not decisive because to reach a definitive conclusion we have to have at least twenty patients.

  - We will add control subjects to our data base. The fact of having patients of Parkinson's disease as well as control subjects would allow to do a classification. This is very important because it would really help in medical diagnosis of this disease. The classification can be achieved through a SVM which separates a given labeled training dataset with a hyperplane that is maximally distant from the two classes, being these classes the patients and control subjects (or patients with different levels of the disease). The objective is to build a function using training data that will correctly classify new examples.

- We will test others kinds of algorithms to obtain features of the gait data. One of them is ICA (Independent Component Analysis). ICA is a statistical technique that represents multidimensional random vector as a linear combination of nongaussian random variables (independent component) that are as independent as possible. ICA is somewhat similar to PCA to extract features. However, it would be interesting to compare both ICA and PCA to determine if we can extract the same information using both methods.

- In addition, all the work developed in this project could be used in other applications. For example in patients with motor disorders or elderly people and establish if this study can be a widespread procedure to others fields.

- **Classification of force data**

  The classification has been done with force data while subjects (both patients and control subjects) were walking normally. We will try to do the classification with other types of experiments where subjects are carrying out different activities. It would allow us to extend the study to whatever daily activity.

- **Qualisys system and Gait Watch (treadmill experiment)**

  - As in the first case, we will increase the data base. This not only allows to have more accurate results but also we can do others types of studies to deepen the knowledge of the Posturographic Body-sway with inertial data.

  - We will analyse the movements not only of shanks and thighs but also of trunk and arms carrying out other experiments with Qualisys System and Gait Watch.

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Appendices