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DESIGN, DEVELOPMENT, CHARACTERIZATION AND DEPLOYMENT OF A GROUND REACTION FORCE MONITORING SYSTEM FOR GAIT ANALYSIS

THESIS

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Abstract

Gait has a strong relationship with the neurological and biomechanical states of our body. This relationship enables gait analysis as a powerful tool to develop auxiliary applications for clinical diagnosis and rehabilitation. On the present thesis, the design, development, characterization, and deployment of a system to monitor and analyze the ground reaction forces (GRF) produced during gait is described. The developed device consists of a sensor footwear integrated with Force Sensing Resistors (FSRs). The sensor footwear has two different modes: real time wireless transmission mode, and datalogger mode.

Furthermore, as far as we know, the importance of in-shoe sensor characterization was not reported in the literature, so we demonstrated the importance of in-shoe sensor characterization to compensate the error contributed by the inherent variability of the footwear's sole to the force/pressure measurements. Additionally, a self-calibrating algorithm was proposed and implemented on the sensor footwear to dynamically adapt the Force Measurement Range (FMR) of the sensors depending on the user's weight. The self-calibration algorithm improved the force measurements' resolution up to 16.66 times. Moreover, gait monitoring software for PC and smartphones (Android) was developed. The PC software was designed as a tool to visualize the GRF produced during gait on real time in consulting and rehabilitation rooms. The smartphone app was designed to take advantage of the datalogging mode of the sensor footwear to enable gait monitoring during daily life activities. Finally, the system was deployed on the consulting room of a specialist in Rheumatology, where it was tested during three months with real patients. During this assessment period, the system was used to acquire tests from 70 patients, thus, demonstrating the capabilities of the system to operate in clinical applications. Feedback from both patients and specialist will be used to improve the system on future work.

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CHAPTER 1:

INTRODUCTION

1.1 BACKGROUND

Most people take the gait for granted, as we perform it effortlessly most of the time and even unconsciously. However, if we observe the gait carefully, it may tell us a lot of things. For instance, the gait can be an indicator of the physiological and neurological state of a person, as is the result of complex interactions of neurological and biomechanical processes. When studying gait, several parameters are monitored, such as ground reaction forces and how these loads distribute along the foot (plantar pressure distribution), joint moments and angles, gait-phases' times, etc. If we monitored the gait from a large group of individuals, we could reach the conclusion that every individual has its own characteristic gait style, to the extent that people or an algorithm could distinguish an individual from its gait; but also, at the same time, we would see some patterns emerge from the group, we would find standard ranges of angular motion of the joints, standard ranges of ground reaction forces on the feet, etc. Patterns that we could stablish as normal. Then, there would be also measurements outside the normal ranges, and it could be due to diverse causes, for example, joint misalignment or wear, physical injury or sequels from it, neurological pathologies, among other reasons.

It is extraordinary that even with these pathologies, the body adapts to achieve balance and coordination to walk. However, the fact that we can walk successfully from point A to B does not mean that everything is OK. But then, why is it so important to maintain a normal gait, if our body is able to adapt to achieve the balance to walk anyway? The human body has adapted through ages to our current physiology and biomechanics, and as mentioned before, there are certain ground reaction force distribution patterns, joint moments and angles, that lead to an efficient distribution of the load on the joints: when the loads at which the foot is subjected are distributed on an "unnatural" way, the forces cause a pathologic stress in the lower limb joints, which they can endure, and may not cause an immediate hazard, but in the long term, these pathologic load distributions cause an accelerated wear on the joints, leading to rheumatic disorders, causing pain, and on the most severe cases, disability.

1.2 PROBLEM DEFINITION

With such a strong relation between the gait and many pathologies, the potential of gait monitoring and analysis to develop diagnosis tools and improve quality of life has developed an interest in many research groups. The research and development of gait monitoring tools commenced with force plate technologies, from static force plates to sensor treadmills. Then, as wireless technologies such as Bluetooth emerged, the development of wearable sensors popularized, and also with the advances on computer hardware and artificial vision algorithms, powerful vision systems also arrived to the gait research scene. Each group with its own strengths and weaknesses has already demonstrated to be useful in applications like the study and monitoring of patients who suffer from Parkinson’s disease, the study of plantar pressure distribution on diabetic feet, fall risk evaluation on elder people, osteoarthritis, among many other applications.

Nowadays, motion capture systems and force plates are the most used technologies on gait analysis. Both technologies achieve high accuracy on their respective areas, vision systems on kinematic measurements, and force plates on kinetic measurements. However, both force plates and vision systems have two main limitations, the first one is the cost of these systems, and the second one is that they need to be pre-installed in the place that they will operate, which disables its usability on real life applications.

1.3 JUSTIFICATION

One of the most important advantages of sensor footwear and other wearable sensors is their versatility to be used outside highly controlled conditions, in contrast with force plates and vision systems; this is especially important for the implementation of gait monitoring and analysis on real life applications. To achieve this goal, research groups have focused on several areas of the development of sensor footwear and other wearable systems. For example, the development of accurate sensors or methodologies to achieve better accuracy on existent sensors, calibration methodologies, energy efficiency of the system, aesthetics, comfort, and social acceptance of wearable sensors.

In this work, we propose a gait monitoring and analysis system. The design, development, characterization, and implementation of a self-calibrating sensor footwear is presented. Also, the development of a PC and mobile software for gait monitoring and analysis is described, the software allows the user to record the gait and subsequently segment the gait relevant data of the recorded tests and standardize it for analysis. We also demonstrate a proof of concept of an application of gait classification using machine learning algorithms.

1.4 OBJECTIVES OF THE RESEARCH

1.4.1 General objective

Design, develop, characterize and deploy a monitoring and analysis system to record and analyze the ground reaction forces of the foot produced during gait.

1.4.2 Specific objectives

- Research the wearable gait monitoring literature.
- Design and develop a low-cost sensor footwear.
- Characterize the developed sensor footwear.
- Develop PC and mobile gait monitoring software.
- Deploy the gait monitoring system on a consulting room.
- Develop a gait-data pre-processing pipeline.
- Demonstrate a proof of concept of a gait analysis application using machine learning algorithms.

1.5 HYPOTHESIS

Gait plantar pressure distribution patterns can be identified and classified through the development and implementation of a sensor footwear-based monitoring system.

1.6 EXPECTED RESULTS

We organized the research project into two main stages:

1. The first stage consists on the design, development and characterization of a gait monitoring system, the expected results for this stage are the following products:
   - Sensor footwear
   - PC Monitoring software
   - Smartphone application
   - Journal article
2. The second stage consists on the deployment of the system on a consulting room, data acquisition, and data analyzing to create a gait preprocessing pipeline. The expected product of this stage is:
   - Data preprocessing pipeline

1.7 CONTENT DESCRIPTION

In this chapter, a brief introduction about the gait has been presented, we expose our view on the potential impact of the applications of gait monitoring and analysis to highlight the importance of the field and to justify the work we are about to present. The thesis is divided into eight chapters. A brief description of the following chapters is shown below:

In **chapter 2,** the core concepts and theories to understand this work are presented, among the topics presented, we write about the lower limb biomechanics and how all their components influence on the gait, it is also described in detail, the gait, its phases, and the parameters to quantitively analyze it, also a description of the machine learning algorithms implemented to develop our analysis tools is presented, and many other topics relevant to the present research.

In **chapter 3**, the history of the development of gait monitoring systems is presented, it is focused on the development of sensor footwear and insoles. Then, divided in two, relevant literature is presented: development of gait monitoring tools, and applications of gait analysis. About the former, sensor configurations, characterization, and calibration, among other aspects are highlighted, and for the latter, the gait analysis applications and their methodologies are classified. On this chapter, we expose some of the goals of the field of gait monitoring and analysis.

In **chapter 4**, the design, development, and characterization of a sensor footwear is presented. All the designs, considerations, and methods to build our device are described in this chapter. Also, we contribute to the field with the proposition of a self-calibrating algorithm to optimize the sensors' resolution depending on the user's weight. Another contribution of this work, as it has not been reported before, is the demonstration of the importance of in-shoe sensor characterization for applications where objective comparisons between subject measurements are needed because of the variability of sensor response due to the inherent variability of the footwear sole (even on flattened-sole footwear).

In **chapter 5**, we present the operating modes of our gait monitoring system. The technical aspects about networking and software development are described. The main focus of the chapter is the description of the features of the software, the data flow of the system, and how the software and the system as a whole is intended to be used in real-life applications.

In **chapter 6**, the methodologies to acquire our data are presented. Also, the algorithms used for filtering, segmenting, and standardizing our data are described. Finally, a proof of concept of classification of plantar pressure distribution pathologies is demonstrated using data obtained with our system and machine learning algorithms.

In **chapter 7**, the final results of our research work are resumed: the developed plantar pressure monitoring system, software, algorithms and methodologies. We also discuss our results and highlight the strengths and weaknesses of our developed system in comparison to systems of the literature. We also discuss how our proposals can contribute on the current state of the gait monitoring and analysis field. Finally, in **chapter 8**, we present the conclusion of the thesis, and state the future work for this project.

CHAPTER 2:

THEORETICAL FRAMEWORK

2.1 INTRODUCTION

In this chapter, the core concepts of the thesis are described. First, the definitions of gait and gait analysis are stated according to the clinical gait analysis literature. Also, the main aim of gait analysis is presented. Then, the most used phases and spatio-temporal parameters of gait are described, as they are often a starting point when analyzing gait in a variety of applications.

Then, the behavior of ground reaction forces (GRF) and how they distribute along the foot during gait (Plantar Pressure Distribution) is described. Afterwards, some basic concepts of statistics and measurement theory are presented. And finally, some factors that add variability to the gait measurements are mentioned, such as design of the sensor system, and inherent variability on the gait of the individuals, these factors are to be considered when designing clinical studies to minimize both systematic and random errors and obtain better results when analyzing gait.

2.2 THE GAIT

Gait is a skill often learned through countless hours of practice during our childhood. Gait can be defined as the cyclic motion of limbs to move the body forward. This cyclic motion is integrated by a sequence of coordinated movement patterns that move the body from one point to another while supporting and transferring the weight of the body [1]. For the joints to move, the muscles produce forces to pull the bones, the muscle signals are sent by the nervous system, which integrates multisensory data (i.e., visual, vestibular sensations, etc.) to achieve constant adaptability during gait to compensate speed, terrain and other perturbations [2].

To fully understand gait, and analyze it, there are core concepts that must be explained. In the following sections, concepts such as the gait cycle and its main spatial-temporal parameters are described. First, a definition of gait analysis and its objective is presented.

2.2.1 Gait analysis

The definition of Stergiou states that gait analysis is a set of procedures to observe, record, analyze, and interpret movement patterns performed as part of the skill of gait [1]. Through history, the main objective of gait analysis has been to gather information to characterize normal gait in order to understand human locomotion to identify impairments and functional limitations that contribute to disability during locomotion [3], and evaluate the outcome of interventions and rehabilitation procedures [4]. Clinical gait analysis can then be further defined as the process of recording and interpreting biomechanical measurements of gait to understand the effects of disease and dysfunction [5].

Understanding the causes and effects of specific perturbations in one of the systems that control gait can be difficult, because for example, perturbations in the neural system may be partially compensated by other structures and alter function leading to new adaptations and changes that are evaluated through clinical gait analysis [6].

There are two main approaches to analyze gait, the cause-and-effect approach (top-down), and the inverse dynamics approach (bottom-top).

Cause-and-effect:

In the top-down approach, the control of gait may be described as follows [7]:

1. First, the sensorial information is processed, and commands are sent by the central nervous system.
2. Then, the signals are transmitted through the peripheral nervous system.
3. These signals cause contraction of the muscles, which generate forces.
4. Subsequently, the application of the forces on the bones generate moments across joints.
5. Then, these moments and forces are regulated according to skeletal segments' anthropometry.
6. Afterwards, movement of the limbs is produced.
7. Finally, ground reaction forces are generated.

Inverse dynamics

In this approach, the control of gait is examined from bottom to top. First, data such as ground reaction forces, joint angles, among other information is collected with gait monitoring systems, such as wearable sensors, vision system setups, force plates, or combinations of them. Then, dynamic formulations are used to determine reaction forces transmitted between segments and the net moments-of-force resulting from muscle activity [8].

With all this in mind, it is clear that through gait analysis, it is possible to create diagnostic tools, to evaluate and improve rehabilitation procedures, and develop tools to monitor and quantify the evolution of gait of patients. Before achieving this, there is terminology that should be clear, starting with the gait cycle and its phases.

2.2.2 Gait cycle and its phases

The gait cycle starts from the instant where one foot makes contact with the ground and ends when the same foot makes contact again with the ground [1]. Most frequently, the gait cycle is divided into two periods:

- The stance period, in which the foot is in contact with the ground,

- The swing period, in which the same foot is in the air.

Additionally, during the stance period, there is a period of time in which only one foot is on the ground (single support), and also a period of time where both feet are in contact with the ground, which is called the double support period.

Then, these periods are divided into phases. For example, from the approach of Rose & Gamble [1], [9], the gait cycle is shown in Figure 2.1, and it is also divided into the following phases:

1. **Initial contact** (0% - 2% of the gait cycle): Initial contact, as its name states, is the phase where the heel makes the first contact with the ground. It is the beginning of the stance period and the first part of the initial double support period.
2. **Loading response** (2% - 12% of the gait cycle): Is the rest of the initial double support period. During this phase, the weight acceptance is completed.
3. **Midstance** (12% - 31% of the gait cycle): This is the first part of the single support period. The end of this phase is distinguished by the occurrence of the “valley” or the local minimum of the vertical ground reaction force.
4. **Terminal stance** (31% - 50% of the gait cycle): This is the second part of the single-leg support period. The center of gravity “falls” from its highest point and potential energy transfers to kinetic energy.
5. **Pre-swing** (50% - 60% of the gait cycle): In this phase, the terminal double support occurs and it is our second loading period. In terms of the vertical ground reaction force, we have the occurrence of the second loading peak.
6. **Initial swing** (60% - 73% of the gait cycle): This is the first part of the swing period, where the foot leaves the ground and flexes the entire leg.
7. **Midswing** (74% - 87% of the gait cycle). This is the second part of the swing period, where the opposite foot leg is in single support with a small base of support.
8. **Terminal swing** (85% - 100% of the gait cycle). This is the third and last part of the swing, and ends when the foot enters again the initial contact phase.

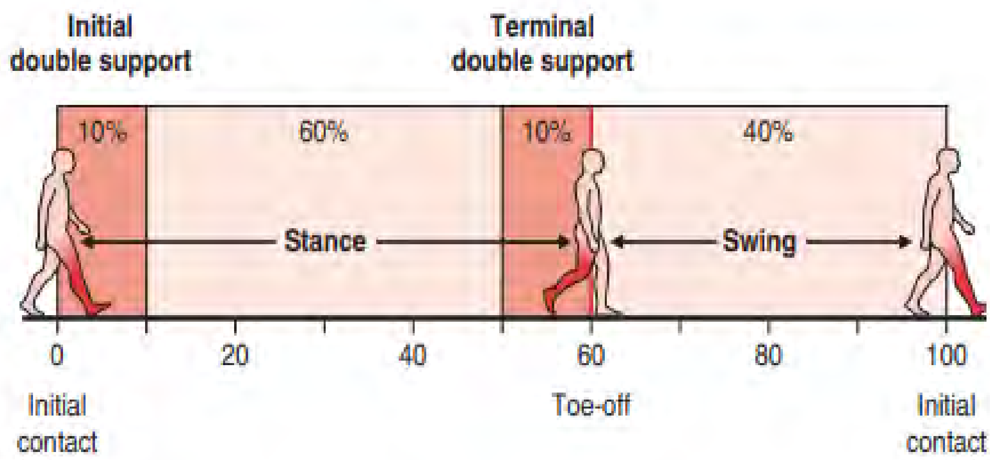


Figure 2.1. Gait cycle and its phases. (Image from C. Kirtley [11]).

The periods and gait phases described above are used to analyze gait and are important flags to observe. The gait phases are evaluated with different measures, most commonly, the spatio temporal parameters of gait.

2.2.3 Spatio Temporal parameters of gait

In table 2.1, some parameters and their definitions are shown [1]:

Table 2.1

Spatio-temporal parameters of gait

Parameter	Definition
Step length	The distance between the point of initial contact of the ipsilateral foot and the point of initial contact of the contralateral foot.
Stride length	The distance between successive ground contacts of the same foot.
Stride time	The time elapsed between foot contact of a leg to the following foot contact of the same leg (Gait cycle duration).
Cadence	The rate of change in distance with respect to time.
Gait speed	This is defined as the rate of change in distance with respect to time (speed = distance/time).

Step width	The distance between the centers of the feet during double support when both feet are in contact with the ground.

There are other gait parameters regarding to the joints of the lower limb, some of them can be extracted directly from GRF data, inertial measurements, vision systems, or combinations of the previously mentioned. Nevertheless, the gait applications presented on this work are not based on spatio-temporal parameters, though, they are very important concepts on the field that we should know.

The work developed on this thesis project, is focused on the monitoring of the ground reaction forces, on the section below, the behavior of these forces during gait is described.

2.3 GROUND REACTION FORCE ON GAIT

As we know, according to Newton's third law, any applied force results in a reaction of equal magnitude and opposite direction. The GRF is exerted by the ground on a body in contact with it. For instance, when a person is standing still, the GRF's magnitude is equal to the body weight of the individual, and the direction of the GRF is perpendicular to the ground. However, when the individual is walking, the GRF increase or decrease due to acceleration forces. The GRF has three components (Figure 2.2):

- Two horizontal components, which are produced due to friction between the foot and the ground, also called shear forces. The shear force that acts anteriorly on the ground produces a posterior reaction (Anterior-Posterior shear (F_x)) and the shear force that acts medially produces a lateral reaction (Medial-Lateral shear (F_y)).

- One vertical component, which acts perpendicularly to the ground (F_z).

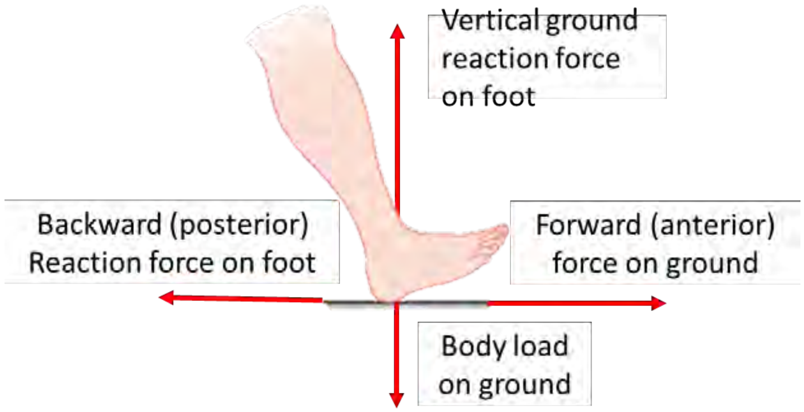


Figure 2.2. Components of GRF vector (Image modified from [11]).

During normal gait, the three components of the GRFs behave as shown in Figure 2.3.

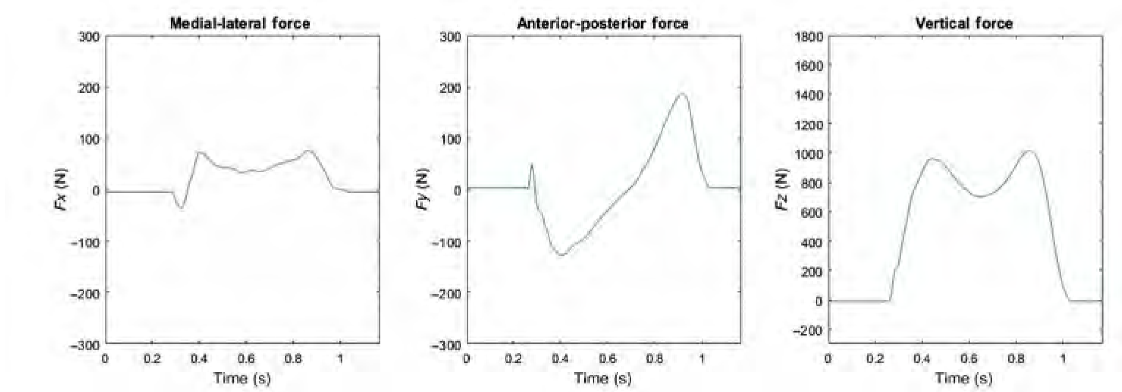


Figure 2.3. Behavior of GRF vector on a gait cycle (Image from Stergiou [1]).

It can be observed that the medial-lateral and anterior-posterior forces can be 10 or 5 times smaller than the vertical force. This, of course does not diminish the contribution of those components to the gait analysis. Traditionally, the medial-lateral and anterior-posterior forces were only detected on force plates systems, nowadays, we can find some wearable sensors that can detect them. For this work, we will focus on the vertical component of the GRF. The vertical component can give us important data, such as critical points to identify the gait phases (Figure 2.4). Notice what happens in each of the time periods A to E:

A. During initial double support, the force quickly rises as weight is transferred from the contralateral limb.
B. The force rises above resting body weight in early stance.
C. The force falls below resting body weight during mid-stance.
D. The force rises above resting body weight once again in late stance.

E. During terminal double support, the force quickly falls as weight is transferred to the contralateral limb.

F. Swing phase: the foot is off the ground so there is no ground reaction force.

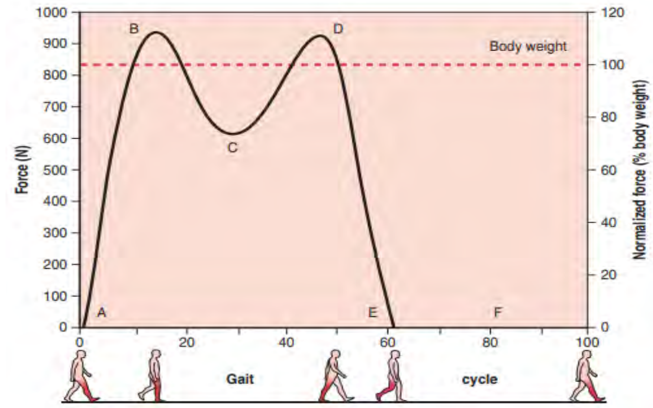


Figure 2.4. Critical points of the vertical component of the GRF (Image from C. Kirtley [11]).

Giakas and Baltzopoulos measured and presented normative ranges for the mean and the standard deviation of the critical points of the GRF (in percentage body weight), along with the time (in percentage gait cycle) at which the peak occurs. The results obtained by these researchers are shown in Table 2.2 [10].

Table 2.2

Normative ranges for the peak forces of critical points of GRF

Force	Mean ± 1 σ	Time (% cycle)	Mean ± 1 σ
F_B	117 ± 9	T_B	23 ± 2
F_C	75 ± 6	T_C	48 ± 3
F_D	109 ± 5	F_D	76 ± 2

The normative ranges provided by Giakas & Baltzopoulos [10] could help as a reference of what to expect when monitoring GRF during normal gait. However, if we try to consider it as a standard to determine normal and abnormal measurements we could incur into false positive or false negative mistakes. Before defining normative ranges, we must ensure that our monitoring systems are accurate and precise. Furthermore, we should carefully design methodologies that minimize the inherent variability of gait (age, gait speed, etc.). We will talk about that on sections 2.5 and 2.6, also on chapters 4 and 6, where the contributions we made on this work to minimize variability on our experiments are described.

Now, let us review how the GRF distributes along the foot.

2.4 PLANTAR PRESSURE DISTRIBUTION

In general, how the load distribute depends on the foot structure and some gait parameters. For instance, heel pressure is affected by heel-strike velocity, longitudinal arch structure, thickness of the heel pad and age. Midfoot pressure is determined by arch structure, while metatarsal head pressure is mainly affected by talocrural joint motion and the gastrocnemius' muscle activity [11], [12]. In Figure 2.5, the plantar pressure distribution behavior during normal gait is shown, as presented by measurements of Novel GmbH [11].

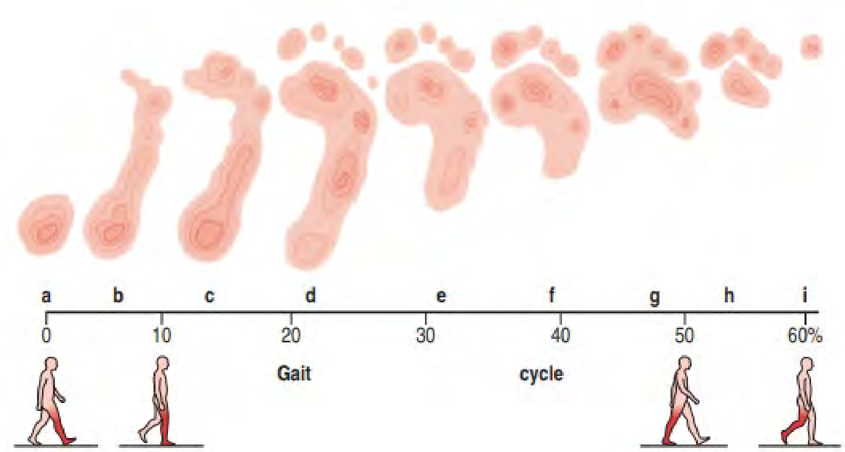


Figure 2.5. Plantar pressure distribution during normal gait (Image from C. Kirtley [11]).

The graph of Figure 2.5 serves as a good reference to recognize where the maximum pressure is applied during normal gait, which could be useful to identify pressure anomalies during each gait phase.

Mueller and Maluf identified basic tissue responses to increased pressure: atrophy, hypertrophy (callus formation), injury (ulcer formation), death (necrosis) [13].
Moreover, injury can occur due to exposure of extremely high pressures resulting from trauma, and repetitive pressures of moderate magnitude repeated thousands of times (i.e.

such as might come from walking) [14]. The monitoring of the foot pressures is often studied on patients who suffer of diabetic neuropathy; the patient feet may lose sensitivity to plantar pressures, and if pathological plantar pressure distribution patterns persist during long periods, the patient feet may suffer from injuries.

Moving on, another parameter that is often studied in clinical gait analysis is the center of pressure, which is the mean of all the pressure applied to the sole of the foot. The trajectory of the center of pressure during normal gait is shown in Figure 2.6, [11].

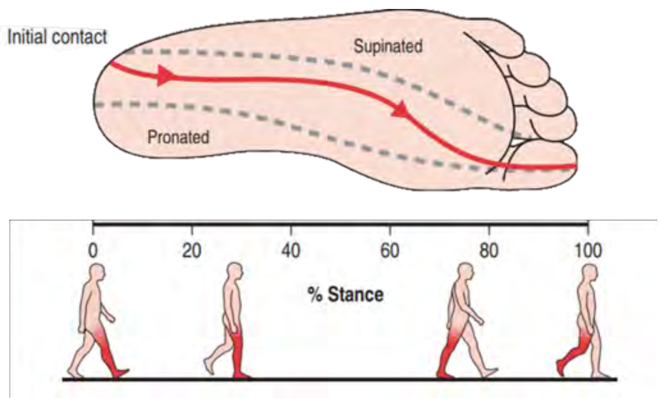


Figure 2.6. Pathway of center of pressure in normal gait (Image from C. Kirtley [11]).

During the stance period, the center of pressure moves from the lateral border of the heel at initial contact, along the foot to the big toe (hallux) at toe-off. The center of pressure can be used to study postural stability, and thus, to potentially detect motor dysfunctions.

Now that the variables that we will be measuring with the monitoring system were presented, we will talk about some considerations that we should make when taking measurements for gait analysis.

2.5 MEASUREMENT THEORY

To develop accurate monitoring systems and analyzing gait with them, it will be necessary to make a lot of measurements and interpret them. However, to reach the correct conclusions about our system, or about the measurements taken with it, we need to remember some basic concepts.

First of all, we should recognize how the measurements are distributed. According to [11], it is safe to assume that gait measurements are normally distributed. The most important parameters for a normal distribution are the mean and the standard deviation. The mean is the sum of all the measurements divided by number of measurements:

$$\overline{X} = \frac{\sum X}{n} \tag{2.1}$$

The mean gives a good estimate of the tendency of the value we are trying to obtain with the experiment; however, it is not enough information to describe the experiment. There is also the spread of the measurements' distribution, which indicates how much confidence should be placed in the estimated mean value. This spread is called the standard deviation (σ). The standard deviation is calculated with the Equation 2.2.

$$\sigma = \frac{\sqrt{\sum |x\text{-}\bar{x}|^2}}{n} \tag{2.2}$$

The standard deviation represents the statistical uncertainty of a measurement, we should remember that the σ is a combination of mainly two factors:

- ✓ Variation in the quantity being measured (time, force, cadence, etc.).
- ✓ Variation or imprecision in the instrument.

In practice, almost all gait measurements are affected by these two factors, so it is important to understand the σ and its possible causes. Now that we understand the mean and the standard deviation, let us take a look at the normal distribution (Figure 2.7).

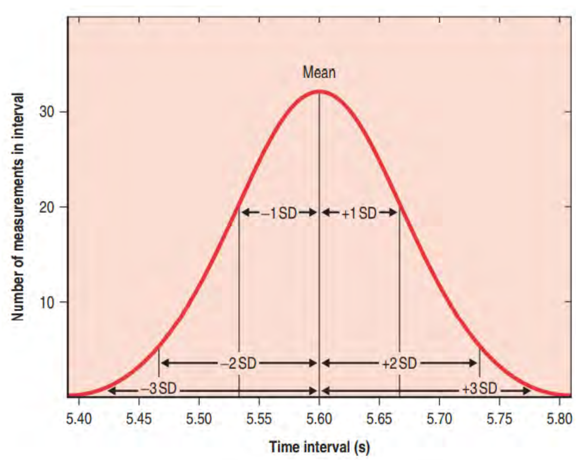


Figure 2.7. Normal distribution (Image from C. Kirtley [11]).

At the middle of the normal distribution, the mean can be found. Then, the 67% of all the measurements fall within ± 1 σ of the mean, 95% fall within ± 2 σ, and 99.7% within ± 3 σ (Figure 2.7), the measurements that fall outside the σ ranges are considered abnormal.

Nevertheless, defining a normative range it’s not straightforward. If we use a ± 1 σ for our normative ranges, and a measurement falls outside these limits, it could still be normal, but with a high or low deviation to the mean due to natural biological variation or instrument imprecision; classifying such a result as abnormal would constitute making what is known as a false positive mistake. On the other hand, if we make normative ranges based on mean ± 2 or 3 σ, some abnormal measurements could fall inside the limits and would be considered normal, which results on a mistake known as a false negative.

Gait measurements often have large standard deviations due to the two sources of variability (biological and instrument), and as of this time, this problem remains unsolved, and most gait laboratories routinely use normative ranges based on mean ± 1 σ, which is unsatisfactory. Contributions to the data collection procedures and improvements on measurement system may improve the variability problem, which would significantly reduce the probability of false negative mistakes, and the normative ranges could be tightened [11].

Finally, it is often desirable to compare the σ of different types of measurements, which makes no sense if the means of each measurement are different (because the size of the σ is often related to the size of the mean) [11]. To get around this, another measure is commonly used, the so-called the coefficient of variation.
The coefficient of variation is the ratio of the standard deviation to the mean, expressed as a percentage:

$$\mathrm{CV}\ (\%) = \frac{100\sigma}{\bar{\mathrm{X}}} \tag{2.3}$$

Now that we understand that every measurement is uncertain to some extent. We can classify these uncertainties, or errors, into two kinds: random and systematic.

Random Error

Random errors may occur due to imprecisions in the measurements’ tools, inconsistencies in experimenter measurements, or due to differences between the participants of the experiment, the surroundings, or the experimental procedures.

However, if the experimenter is trained, and designs adequately the experimental procedures, the random error could be minimized to the imprecisions of the instrument, which depends on its quality, and of course also due to the inherent variability between participants of the experiment. To estimate the 'correct' value for the measurement of an experiment, we calculate the average or mean. The silver lining of the random error is that, though it adds variability to the data (increasing the spread of the distribution), it does not affect the mean (Figure 2.8a), because each measurement is just as likely to be lower or higher to the mean.

Unfortunately, there is another type of error: systematic error (Figure 2.8b), which causes the mean to deviate from its true value, introducing a bias into the measurement.

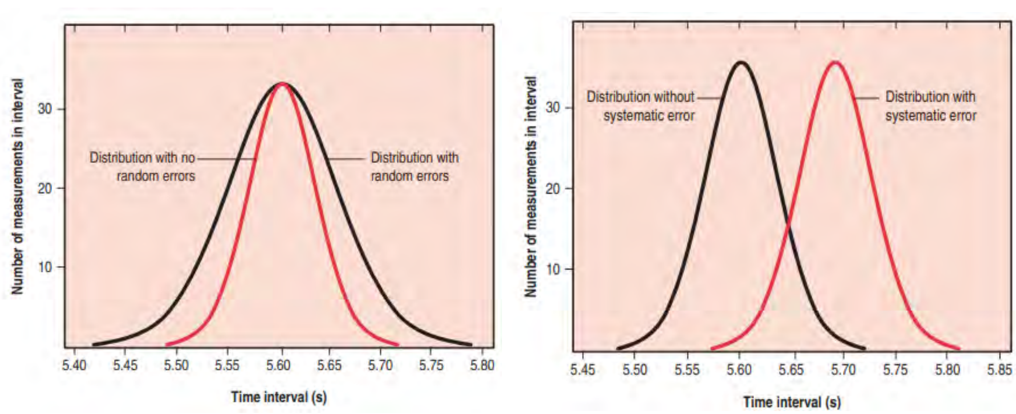


Figure 2.8. The effect of a) random error b) systematic error (Images from Kirtley [11]).

Systematic error

The systematic error is usually a much more difficult error to deal with, because it can't be removed by averaging. The only solution would be to estimate the bias and subtract it from all the measurements. There are many examples of systematic errors in gait measurements, sometimes they can be reduced or eliminated by careful design of equipment, but some errors remain and many researchers are working to try to tackle them [11].

In the following section, some examples of relevant gait variability are described and some solutions on how to minimize variability in gait experiments are mentioned.

2.6 VARIABILITY ON GAIT MEASUREMENTS

When measuring normal gait, at least two main sources of variability should be considered:

- ✓ Gait variability between individuals due to age, mood, among other physiological and psychological factors
- ✓ Variability due to imprecisions of the gait monitoring systems.

2.6.1 Gait variability

One of the factors that should be definitely considered when studying gait, is the walking speed. The walking speed affects the amplitude of the ground reaction forces significantly during the early and mid-phases of the stance period, as shown by Stansfield et al [11], [15].

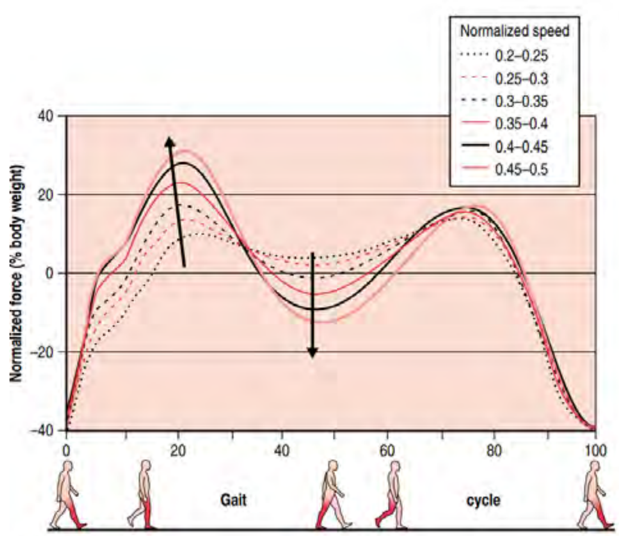


Figure 2.9. Effect of speed on GRF (Image from C. Kirtley [11]).

Also, peak plantar pressures are generally increased with walking speed, especially under the heel, 1st metatarsal, lateral forefoot and hallux. On the other hand, pressure falls under lateral midfoot, and there is a tendency for loading to shift medially [16].

Among some aspects that affect the walking speed of the individuals is the age, where the mean walking speed decreases as age increases. Also, mood affects the walking speed. Sloman et al. found, that mood not only affects the walking speed but also generates fluctuations in the GRF, as they measured that depressed people seem to have a less pronounced M-shape on their GRF profiles. This is caused due to low acceleration forces generated by the individuals while walking (less energetic gait) [17].

Other factors were inversely correlated with the amplitude of the GRF, for instance, the correlation coefficients (r) for mood, sleep disturbance and indecisiveness were $r = -0.32$, $r = -0.46$, and $r = -0.38$ respectively. Although the findings are likely due to the depressed subjects walking more slowly [18], they do reveal an interesting relationship between motion and emotion [11].

2.6.2 Sensor imprecisions

We already know that the monitoring systems may affect the variability on gait measurements. On Table 2.3, some inherent characteristics of sensors used for force/pressure monitoring that may affect on gait measurements are enlisted:

Table 2.3

Parameters used to characterize sensor's performance

Parameter	Definition
Accuracy	The maximum difference between the actual (known) pressure (as measured by some gold standard technique) and that measured by the sensor, expressed as a percentage of the calibrated range of the sensor.
Linearity	The maximum discrepancy between sensor readings from a straight line (linear regression).
Hysteresis	The difference between the measured pressure during loading compared to that measured during unloading.
Creep or Drift	The tendency of a sensor reading to gradually change over time when a constant load is applied.
Dynamic response	The ability of the sensor to respond to rapid changes in loading (i.e., when initial contact occurs).
Curvature artefacts	The effect of bending of the sensors on the measurements (artefacts).

Crosstalk	The effect that a load applied to one sensor affects the readings from those adjacent to it.
Temperature	The effect of temperature on the sensor's response

These characteristics affect differently the sensors depending on the technology they are based (resistive, capacitive, piezo-electric, piezo-resistive, optical, etc.). Undoubtedly, a proper sensor characterization is the key to minimize both random and systematic errors from the sensor systems.

On the following section, a brief description of the contribution of this work to address this variability is presented, including the references to the chapters where the contributions are described.

2.6.3 Minimizing variability

When analyzing gait, what we want is to be able to effectively identify abnormal measurements. Previously in Section 2.5, it was mentioned that defining normative ranges is a difficult task to perform. This is due to the variability of the gait measurements because of the inherent variability of gait, acquisition methodologies, and the monitoring instruments which add both bias and spread to the measurements. Classifying in such conditions may incur in many false positive and false negative mistakes, which is naturally unacceptable for clinical applications.

To define more robust normative ranges, we must minimize all sources of variability, in this project, we have addressed this with the following contributions:

- ✓ Monitoring system (Chapter 4):
  - ❖ Considerations on the design of sensor array to avoid mechanical error, and possible sensor bending.
  - ❖ Development of a self-calibrating algorithm that optimizes the sensor resolution depending on the user's weight.
  - ❖ Extensive in-shoe characterization, which compensates the inherent variability that the footwear contributes to the measurements.
- ✓ Gait acquisition and methodology (Chapter 6):

  - ❖ Proposition of a gait acquisition methodology that minimizes variability regarding walking speed without interfering with the natural gait of the participants.
- ✓ Data preprocessing (Chapter 6):
  - ❖ Development of a gait preprocessing pipeline that automatically removes the first and last step of the gait (which have different acceleration forces compared to the average step of the gait), and segments the relevant steps for further analysis.

Additionally, for every study, the participants must fulfill requirements in age, weight, height ranges, among other factors that may increase variability in measurements.

2.7 CONCLUSION OF THE CHAPTER

On this chapter, the core concepts needed to understand the contributions made on this thesis project were presented. First, a definition of gait was stated, followed by a definition of gait analysis, highlighting its main objectives, and describing the approaches used on gait analysis. Furthermore, the gait cycle and its phases were described. These phases are often used to obtain spatio-temporal parameters of gait , which are used to characterize normal and pathological gait. Afterwards, measurement theory was presented to understand the variability found when measuring gait. Finally, the two main sources of variability on gait measurements were presented, as well as a small discussion of how the variability may be minimized.

CHAPTER 3:
STATE OF THE ART

3.1 INTRODUCTION

In this chapter, a part of the history of the development of gait monitoring systems (GMS) is presented, the history presented in this chapter is mainly focused on ground reaction force (GRF) and plantar pressure distribution (PPD) monitoring systems. Then, a classification of the GMS is presented, the main strengths and weaknesses of current approaches are highlighted, at the end of this section, we discuss about the main applications where the strengths of current approaches may be better exploited.

Then, divided in two main sections, relevant literature about the gait is presented. The first section talks about the development of wearable GMS. In this section a brief description of commercial systems is presented, and then, the section heavily discusses academic systems, focusing on their sensor configurations, characterization and calibration, among other aspects. The second section talks about the applications of gait analysis. In this section, the sensor data needed to achieve the application and the methodology to analyze gait are discussed. Afterwards, gait analysis methodologies based on machine learning technologies are discussed.

By the end of this chapter, the reader will be acquainted with the main groups of GMSs, also the reader will know the main milestones achieved by the wearable GMS and the current goals of research of gait monitoring and analysis.

3.2 HISTORY OF GAIT MONITORING AND ANALYSIS

The following history is a synthesis of Prof. Richard Baker's 2007's article titled: *The history of gait analysis before the advent of modern computers* [19].

It has been found that the first reference of gait analysis was written by the philosopher Aristotle (384–322 BCE) on his work *Aristotle: parts of animals, movement of animals, progression of animals*. One of his propositions was that, when walking, the human head moved slightly down when he bends and goes higher when he stands upright and raises, producing zig-zag motion. This particular idea is correct, however most of his propositions were wrong because they were only theorized but never were tested by experiments.

Mathematical contributions were made in Europe by Girolamo Cardan (1501 - 1576) between 1533 to 1552, with his study of the properties of three-dimensional angles. Between 1564-1642, Galileo Galilei (1564 – 1642) contributed not directly to gait itself, but with its deductive and experimental methodologies in physiology. Rene Descartes (1596 – 1650) on his physiology textbook "De Homine" published on 1662, theorized about closed loop motor control, in which he showed that the limbs were controlled by muscular activity influenced by the nervous system and feedback was provided by the eyes.

Between 1608-1679, one of Galileo's pupils, Giovanni Borelli (1608 – 1679) performed the first experiment in gait analysis, in which he deduced that there was mediolateral movement of the head during walking. Other contributions by Borelli were his studies of the muscle's biomechanics. Despite his advances, he made some mistakes in the physical laws that governed forces, which were formulated properly 9 years after Borelli's death by Isaac Newton (1642 – 1727) in his *Principia Mathematica*.

Then during the 18th and 19th century a series of physiologists made some observations on walking. However, there were two main reasons why their contributions achieved little progress. The first reason was the same mistake as Aristotle did, they did not experiment to corroborate their theories. The second reason was that the authors either had knowledge about mechanics or physiology, but not both.

The next major contribution was made by the Weber brothers (1795 – 1891), who addressed both the physical and physiological backgrounds. In 1836, they published their work *Mechanik der Gehwerkzeuge (Mechanics of the Human Walking Apparatus)* in which they experimented with a stop watch, measuring tape, and a telescope, to draw conclusions about the change of step length and cadence with the walking speed. They also attempted to determine the position of the limbs at 14 instants of the gait cycle, these however, were based mainly on conjecture. For instance, an incorrect conclusion was that the knee is in a considerable degree of flexion at the end of the swing phase, which then was correctly refuted by the physician Guillaume Duchenne (1806 – 1875).

Duchenne was a pioneer of electrophysiology and also made some studies of human movement, he described and located the origin of some lower limb affections, for example the one named after him, the Duchenne muscular dystrophy, also described the Duchenne gait pattern, in which the pelvis raised on the side of the swing limb and there is increased abduction at the stance side hip as a compensation for the absence of functional hip abductors. In 1895, the German surgeon Friederich Trendelenburg (1844 - 1924) also described the Trendelenburg gait pattern, in which the pelvis drops on the swing and there is increased adduction during stance as a compensation for weak abductors.

The next major contributions on human movement were made on the time of the physiologist Étienne-Jules Marey (1830 - 1904). He collaborated with his student Gaston Carlet (1849 - 1892), Carlet developed a sensor footwear with three pressure transducers. He was the first to record and publish the double bump of the ground reaction force. This and other experimental techniques were published in his thesis in 1872, were he concludes with a description of the normal human gait cycle.

Other contributions to gait monitoring by Marey were achieved from the study of horse's gait. At the time, there was a debate about whether or not there is an instant during the horse's trot when all four hooves are off the ground. Marey adapted the Carlet's sensor footwear for horses and demonstrated without a doubt that there is clearly a moment when any hoof is in contact with the ground. This was in Europe, at the same period of time, the photographer Edward Muybridge (1830 – 1904) reached the same conclusion in America with a different gait analysis methodology. Muybridge was aware of Marey´s work and planned to take a series of images of the whole trot. He used a battery of cameras triggered in succession. The pictures were published in *Scientific American* in 1878 and a year later in the French journal *La Nature*, which attracted Marey´s interest.

Marey recognized some limitations of the Muybridge's technique, for example, that this series of images were taken from slightly different angles, which prevented to achieve useful scientific measurements. Therefore, Marey developed the chronophotograph, which enabled several different images to be captured on the same photographic plate. However, this device had also a limitation, the images overlapped and the measurements were still difficult. Marey and his student Georges Demeny (1850 – 1918) developed techniques involving different types of markers, which resulted on a methodology from which they could obtain meaningful measurements. Marey continued to refine his technique and used it to study pathological walking. Marey's work is comprehensively described by Prof. Marta Braun in her work *Picturing Time: The work of Etienne-Jules Marey*.

Around the same period of time, the mathematician Otto Fischer (1861 - 1917) was the first to conduct a three-dimensional gait analysis. He developed an experimental suit in which Geissler tubes strapped were strapped to the joints. During the experiments the subject walked in the night with the suit, the lights on the suit flashed at some frequency, and with a carefully calibrated photographic setup, Fischer captured the subject's gait. Then, points were measured on the images from each of the cameras on the respective side of the subject and a full three-dimensional reconstruction of the true position of the point calculated, and the joint centers were calculated and using a full inverse dynamics approach, he was able to calculate the joint moments for the lower limb joints during the swing phase of the gait.

The methodologies of Fischer remained as the definitive work on kinematics for several decades, but the development of force plates emerged to enable kinetic measurements. Marey and Carlet had developed a pneumatic system to measure in-shoe pressures. And using the same technology Demeny and Marey created a pneumatic force plate, which they used to investigate the energetics of gait. However, Demeny's plate only measured the vertical component. Jules Amar was the first to develop a three-component force plate. Purely mechanical force plates were developed by Wallace Fenn and Elftman in 1930 and 1938 respectively. And in the late 40's, the engineers Cunningham and Brown developed a six-component force plate using strain gauges. It was until 1969, when the first commercially available force plates were designed for biomechanics. They were made of piezoresistive technology by Kistler, and the first commercial force plates that used strain gauges were available in the early 1970s.

Other advances were made at the Biomechanics Lab at the University of California at Berkeley, where a team of 40 scientists and the Committee on Prosthetic Devices was assembled after the second world war to rehabilitee those injured at the war. The team was headed by Verne T. Inman (1905–1980), and Howard D. Eberhart (1906–1993). Their work is documented in the book *Human Limbs and their Substitutes*. The group started with a study of normal locomotion using cine photography and light interrupted photography techniques. This study was based on the principle that understanding the normal gait was a prerequisite of a study of amputee gait. As a consequence of this decision, their work was applicable to many other fields. However, to analyze a single stride, they needed over 14,000 calculations performed by hand, which at first required over 500 man-hours. And so, one of the greatest challenges to establish gait analysis as a clinical tool was to reduce the time of processing, which of course the advances of computers had the biggest impact.

Other advances on gait analysis were achieved through the developments based on the Berkeley's techniques. For instance, the study of gait on 60 normal men conducted by Murray, their conclusion about the relation between the age and height and the variability in gait patterns in adults is still regarded as the definitive work in the subject.

Later on, the development of clinical gait analysis was driven by Richard Sutherland and Jacquelin Perry. They used electromyography to study the gait. During the 1960s and 70s, electromyography took an important role in clinical gait analysis. However, both Perry and Sutherland recognized that it was not enough. Perry complemented the studies using instrumented methods for measuring temporal-spatial parameters.

Some of the final major contributions on the pre-computer era, were the studies made by Larry Lamoreux, who fixed electrogoniometers to a metal exoskeletal frame to measure three-dimensional angles at the hip, and one-dimensional angles at the knee and ankle. But even by the end of the 70s, instrumented gait analysis was still mostly being a research tool as equipment was generally cumbersome and time-consuming to use.

3.3 THE GAIT MONITORING SYSTEM CLASSIFICATION

There are several techniques used in gait analysis. These techniques use technologies such as motion capture cameras, optoelectronic systems, inertial systems, electro goniometers, pressure mats, in-shoe force/pressure sensors, force plate mechanisms, electromyography, among others [20]. However, three types of systems are the most used: Platform systems (force plate mechanisms/pressure mats), Vision systems (motion capture cameras), and wearable systems (in-shoe sensors/inertial sensors).

3.3.1 Platform systems

There are two main types of platform systems, fixed force sensing platforms, and portable force/pressure sensing mats.

- **Force plates**

The force platforms often use metal plates with load cells attached to each corner. This mechanism is used to measure the GRF vector caused by the user standing or moving on the platform. Force plate mechanisms can accurately measure the three components of the ground reaction force induced on the plates. Also, as the force plates are placed on a fixed location on the ground, the center of pressure of the subject body can easily be calculated [20].

The main advantage of the force plates is their accuracy on 3D GRF measurements, which can be used alone to identify pathologic GRF patterns. However, data captured from foot plates is often combined with limbs kinematics data from other sensors. The main issue of the force plates is that they are fixed on the ground and their cost, which reduce its use to biomechanics laboratories.

- **Pressure mats**

Gait mats are instrumented carpets with force or pressure sensors. The pressure mats are almost similar to the force plates, but cheaper and not as accurate as force plates, however, pressure mats often measure only the vertical component of the GRF. The characteristics of the mat such as pressure range, sensitivity, and linearity are defined by the technology of the sensors they use (resistive, capacitive, or piezoelectric, piezoresistive, etc.). The geometry of the mat is rectangular, and the length of the mat may have different sizes from less than a meter (to measure one footstep) to several meters to measure walk sessions.

These systems provide better portability than the force plates at a lower cost but also with lower resolution. Most importantly, the pressure mats provide reliable data about foot contact, step and stride length, and plantar pressure distribution.

3.3.2 Vision systems

One of the most used techniques in gait analysis are the motion capture cameras. Many research groups have developed strategies to characterize gait, to develop clinical studies or create gait recognition applications. Some features than can be extracted from motion capture systems are joint positions, joint motion trajectories, joint angles, among others. Gait can be analyzed with or without markers attached to the body. For 2D analysis of gait, a single camera is placed parallel to the user's plane of motion, and for 3D analysis, a complex setup of cameras is needed. Then, sensor fusion and artificial vision processing techniques are used to obtain accurate kinematic and dynamic analysis of gait.

The main advantage of these systems is their accuracy, and the capabilities to extract several gait parameters from the sensor fusion. However, with great power come other limitations, such as the cost of the equipment, the need of very controlled environments (light, focal distance, etc.), also, if markers are used, the technicians need time to place all the markers, and even so, measurement errors may occur if skin artifacts occur due to slippage of the markers. Motion capture systems are powerful tools for gait analysis, however some of their limitations restrict their usage to only gait laboratories.

3.3.3 Wearable systems

Finally, the third most common type of gait monitoring systems are the wearable sensors, the most common types of technologies found in the literature are: inertial based wearables, and sensor footwear/insoles.

- **Inertial systems**

  Inertial systems integrate accelerometers and gyroscopes to provide acceleration and orientation data for gait analysis, for instance, segment acceleration, segment orientation, and joint position [21]. The sensors are small, lightweight, and their detection capabilities are enough to monitor the angular velocity and accelerations during gait.

The major advantages of inertial wearable systems are their portability, and the capability to extract several gait parameters from their data. Some limitations are that the sensors must be attached to the body, which sometimes may be uncomfortable. Also, if skin movement artifacts occur, the data can be affected significantly.

❖ **Sensor Footwear**

In-shoe systems are often found into two types, the first type consists of sensor insoles that are embedded on any shoe. The second type are modified footwear, with sensors integrated to it. The most used sensors on in-shoe wearables are force and pressure sensors, but sometimes, some gyroscopes and accelerometers are also integrated to the shoes. Sensor footwear are used to obtain the vertical component of the GRF, or the plantar pressure distribution, which can be used to characterize the load/pressure patterns of both healthy and pathologic gait. The characteristics of these devices vary from design to design, as multiple choices of sensor quantity, and type of technology are available, also calibration techniques, and general design of the sensor footwear affect its performance.

The advantages of sensor footwear are its high versatility of design and cost and great portability that enables analysis during daily life activities. Some limitations are that they often only measure the vertical component of the GRF. This often leads to the need of combining with limbs kinematic data from inertial systems for complex gait analysis.

3.3.4 Discussion

In the early studies about gait monitoring, force plates were the main gait recording tool, their high spatial resolution and accurate GRF measurements have been their main advantages [22]. Also, vision systems provide accurate gait analysis. During the last decade, great advances on vision systems have been driven by the advances on computer’s hardware and machine learning algorithms [23]–[26].

Today, motion capture systems and force plates are the most used technologies on gait analysis. Both technologies achieve high accuracy on their respective areas, vision systems on kinematic measurements, and force plates on kinetic measurements.

However, both force plates and vision systems have two main limitations, which some research groups are trying to tackle with the development of accurate and portable wearable technologies. A comparison of some aspects of the discussed technologies can be observed on Table 3.1 (extracted and modified from Chen [21]).

Table 3.1

Quantitative systems for gait analysis

Instrument	Motion capture system	Force plate system	Wearable: Inertial sensor	Wearable: Footwear
Measures	Kinematic measurements	Kinetic measurements	Kinematic measurements	Kinetic measurements
System Cost (USD)	> $30,000	$200 - $30,000	< $2000	< $3000
Practicality	Requires pre-installation and expert operation	Requires pre-installation. Fixed to the ground.	Often need strapped-on electronics	Easy to wear
Accuracy and Precision	High	High	Sensor and algorithm dependent	Sensor and algorithm dependent
Continuous monitoring	Less than 10 minutes	Less than 10 minutes	>2 Hours	>2 Hours
Computation cost	High	Low	Low	Low

The first thing that we may notice is that wearable technologies, inertial and sensor footwear, can be used to obtain the gait parameters offered by vision systems and force plates, respectively. The difference in cost between the technologies could alone justify focusing on the development of better sensors, calibrations procedures, and algorithms to achieve wearable systems with the same precision and accuracy as the vision and force plate systems. The cost is an important aspect, but a matter of greater importance to some researchers is the practicality, both vision systems and force plates require to be pre-installed in the room where they will operate, which restricts its usage to gait analysis laboratories.

One of the most important features that the wearable technologies contribute to the gait analysis, is that they enable real time applications on daily life activities. As we are most interested on making these technologies available for consulting and rehabilitation rooms, or for the average user, from now on, we will focus on the literature of wearable technologies for gait analysis, and mostly on sensor insoles and footwear.

3.4 STATE OF THE ART: WEARABLE SYSTEMS

Wearable sensors for gait monitoring are not new, one of the first devices to measure the pressure between the foot and the sole was developed by Carlet G. in 1872 [19], [27]. Then, in 1963, Bauman and Brand presented a technique to measure PPD using thin pressure transducers attached to the foot, this were connected to a box that contained the signal conditioning circuits, the box is attached on the user's waist, and then connected through a cable to the recording system [28]. Then, until the 90s decade, the first wireless in-shoe systems were developed [29]. However, the research of sensor insoles and footwear really started until the wireless technologies popularized. When the 21st century started, the field of wearable sensors for gait monitoring started to grow constantly. After that, it did not take long after some gait monitoring systems became available commercially, targeting gait laboratories and sport analysists.

3.4.1 Commercial systems

Commercial wearable systems often are integrated by sensor insoles, a wireless transmission and datalogger module, and monitoring software (depending on the features may cost extra).

On Table 3.2, some of the commercially available systems for PPD monitoring are shown [30], [31].

Table 3.2

Commercial wearable systems for PPD monitoring

System	Sensing Technology	Number of sensors	Sampling rate	Communication
Pedar [32]	Capacitive	85 - 99	0 – 100 Hz	USB/ SD card/ Bluetooth
F-Scan [33]	Resistive	960	0 – 750 Hz	USB/ datalogger/ Wi-Fi
medilogic WLAN insole [34]	Resistive	240	100 – 400 Hz	Wi-Fi
BioFoot[35]	Piezoelectric	64	50 – 250 Hz	Wireless
FlexinFit[36]	Resistive	214	25 – 50 Hz	Bluetooth
W-inshoe [37]	Resistive	9	100 Hz	Bluetooth

Commercial systems use various types of sensor technology, and number of sensors, ranging from 9 to almost 1000 sensors, sampled from 25 to 750 Hz (tethered or datalogger). A large number of sensors and high sampling rates of course offer insightful gait analysis, however, Munoz-Organero et al. have demonstrated that with a small number of sensors (4 sensors), gait assessment can be done, thus reducing the device's cost [38]. Naturally, the number of sensors and their positions may vary depending on the application, or a specific pathology, but with the optimization in mind, a large number of sensors may seem inefficient, not to mention that some commercial systems can cost up to $5000 USD.

Another limitation of commercial systems is that most of them have bulky electronics strapped-on to the waist or leg, which may affect the natural gait of the user.
Even so, as these commercial systems are designed for research rather than real life applications, its use is not ideal outside of research facilities.

The above limitations have led several research groups to create their own gait monitoring systems, focusing on developing portable, low cost and energy efficient devices, as well as improving measurement accuracy and precision.

3.4.2 Academic Systems

The need for monitoring the load between shoe and foot for clinical applications has driven researchers to develop wearable PPD monitoring technologies which allow acquiring PPD in real life activities. In the quest of a cost-precision tradeoff, over the last decade, researchers have been developing wearable in-shoe systems addressing precision [39], energy consumption [40], [41] portability [42], among other issues leading to a wide variety of monitoring systems varying in quantity, technology and sensor positioning.

Sensor quantity and sensor positioning may vary regarding a specific pathology or application. For instance, with just three force sensors and a gyroscope, an application for the primary gait phase detection has been demonstrated by Passas *et al.* [43]; on diabetic neuropathy patients, heel, toe and metatarsal heads are monitored to prevent ulceration produced by hyper pressure [31]; also with two force sensors, one on the first metatarsal head and the other on the external middle foot zone, the gait variability was measured to monitor post-stroke patients by Muñoz-Organero *et al.*[38]; a sensing insole with eight pressure sensors was used to identify walking strategies developed due to mild pain on knee osteoarthritis patients [44], and many other applications can be found on wearable PPD monitoring literature. Heel, metatarsals and toe are common sensing zones monitored by almost any application. Claverie *et al.* studied and determined 12 optimal zones to obtain an accurate discrete plantar pressure distribution [45].

In-shoe force/pressure sensors are capacitive [46], [47], piezoelectric [42], [48], optical [49], [50], among other types of sensing technologies. One of the most used sensor technologies on PPD monitoring are the resistive technologies [30], [41], [51]–[53]. Force sensing resistors (FSRs) are an effective cost-precision solution in force measurement. FSRs change its resistance when an external force is applied on them, it is worth mentioning that the resistance change is non-linear. Signal conditioning is needed to transform resistance changes into a variable that a microcontroller can read. An easy, but rather inadequate solution are the voltage dividers, which reflect the sensors non-linearity on the voltage signal. Abdelhady *et al.* utilized a transfrequency conditioning circuit to linearize the response of the FSRs [51], however, the circuit is supplied with 15 V which results in bulky electronics affecting the naturality of gait. Solutions based on operational amplifiers like the non-inverted amplifier configuration reduce the sensor´s non-linearity, though the range of force measurement must be carefully chosen to obtain exact and precise force values. A dynamical self-adaptive signal conditioning circuit allows to maximize the sensing resolution for every individual, which is a feature that has not been reported on quantitative PPD literature.

Before we review the contributions of the sensor footwear presented on the literature, we must recognize and separate two main types of applications in which sensor footwear are implemented. Applications that rely on quantitative analysis, and applications that rely on gait-phase transitions or activity detection.

Accuracy and precision

For quantitative analysis, a key aspect of sensor footwear is its sensors' characterization and calibration, which, is rarely mentioned, and when sensor characterization is reported, it is vague; for example, Lin *et al.* [42] developed a 48 piezoresistive sensor insole, but no calibration data for the pressure sensors was presented, Abdelhady *et al.* [51] applied masses from 0.1 to 10 Kg to obtain a voltage vs weight curve, however, they do not state if the characterization is done to the sensors on or off their 3d-printed insole. Individual sensor calibration was reported with load cells outside the shoe by Bamberg *et al.* [53]. Orlin and McPoil presented a technique to calibrate sensor insoles [22], it consists on using an air bladder system to apply uniformly several known levels of pressure, they mention that this allows to effectively generate a calibration curve for a matrix of sensors. Also, sensing insole systems [42], [51], [53], which are designed to be used on any footwear, does not consider that every footwear alters the natural PPD due to the relief of the sole. In-shoe characterization allows compensating the variability on the response of the sensors due to the footwear, improving accuracy on GRF measurements. on applications in which quantitative PPD comparison between patients is needed, results would be affected mainly by two factors: firstly, when using sensor insoles on different shoes, the natural PPD of the individuals would be affected by different reliefs from their footwear, disabling objective comparison between measurements; and secondly, as every footwear have different sole material, relief, and thickness, the accuracy and variability of GRF measurements would be affected.

Now, that the key aspect of sensor footwear for quantitative analysis has been discussed, we can proceed to talk about the factors that are to be considered on both quantitative analysis applications, and gait-phase based applications.

Low cost and power consumption

The low cost of the sensor footwear devices is an import aspect to consider. As one of the main goals and objectives of wearable sensors is to provide monitoring on real life situations, the sensors must be accessible to any rehabilitation and consulting room, and if possible, to the public. For instance, Hua et al. [41] developed a low-cost power efficient sensor footwear with two pressure sensors and an accelerometer. This low-cost setup could be used for activity detection. Also, Wu et al. [40] developed a power efficient sensor insole, which can operate up to 11 hours of continual usage. They achieve this efficiency with low power components, and with local storage of the data, thus, saving power by not utilizing wireless transmitters.

Portability and social acceptance

Portability and social acceptance are also important factors of sensor footwear development. These aspects may not affect the accuracy of the device, but they play an important on role on how viable the wearable technologies are for real life applications. Some works that make a really good work on their designs are [40]–[42], which would allow the natural integration of these devices into the daily life.

In contrast, other devices are designed with cumbersome or bulky electronics that are difficult to integrate to the footwear [39], [49], [51], which need to strap-on some components to the body. This restricts its use on daily life applications.

A perfect wearable device must consider all of these aspects, they need good accuracy and precision, to produce reliable data for clinical ambulatory applications. The devices must be accessible, and also provide functionality for long hours, and finally, the aesthetics and portability, it may not affect the quality of the measurements, but at the end, this factor will be the final judge of the viability of wearable sensors on the daily life.

3.5 STATE OF THE ART: GAIT ANALYSIS

Monitoring and analysis of the intensity of the ground reaction forces (GRFs) to which the human foot is subjected during real life activities such as gait, and how these loads are distributed along the foot (plantar pressure distribution) have been the object of study of research groups due to its role as an auxiliary diagnostic tool of diverse pathologies [54]–[57]. On gait analysis, gait parameters such as ground reaction force (GRF) [49], [58], [59], gait phase times [60], PPD patterns [44], [61], center of pressure [62], among many others are extracted [21], [63]. The monitoring of these parameters have proven useful for clinical studies in a wide variety of medical fields like rehabilitation of post-stroke patients [38], [64], knee pathologies [44], [65], [66], and post-surgery [67], on the study and monitoring of neurological diseases such as Parkinson's disease [41], [68] or cerebral palsy [52], in geriatrics ambulatory applications like fall risk assessment [69], [70], prevention of ulceration on diabetic foot [71], among many others.

As wearable gait monitoring systems continue to improve regarding cost, accuracy, portability, power consumption, comfortability, and social acceptance, more gait analysis applications are proposed.

3.5.1 Applications of gait analysis

On this section, some of the applications presented on the gait analysis literature are reviewed. An extensive recompilation and review of the gait analysis literature can be found on Chen's et al. article [21].

Rehabilitation

One of the most important applications of gait analysis is rehabilitation. As gait is highly correlated to the lower limbs biomechanics, the nervous system, and even the animic state of a person, gait analysis provides a tool to monitor the advance or recovery of many pathologies. Some examples of research works presented in this area are:

- Reed Gurchiek et al. presented an open source algorithm to analyze gait data from accelerometers and electromyography sensors to monitor and quantify the progress of patient rehabilitation after surgical reconstruction of the anterior cruciate ligament. Their approach is to measure gait asymmetries and use statistical methodologies to quantify the evolution of the patient’s rehabilitation [67].

- Zexia He et al. developed a wearable sensor and used it to monitor the kinematic gait parameters to monitor the knee adduction moment (KAM) to assess rehabilitation of osteoarthritis patients [65].

- Nagaraj Hedge and collaborators developed a GRF monitoring sensor footwear and presented a machine learning based activity detection algorithm to monitor the evolution of gait on children with cerebral palsy [52].

- Simona Crea et al. presented a sensor footwear to rehabilitate lower-limb amputees. The device detects the gait phase transitions of the prosthetic leg, and depending on some parameters, some vibrating elements attached to the leg skin give feedback to correct the gait patterns [58].

- Post stroke rehabilitation is also a frequent gait analysis topic on the literature. For example, Fulk et al., have presented a gait activity recognition smartphone app, which quantifies the amount of time of daily activities. When the patient, spends too much time without performing physical activities, the app encourages the patient to walk, which is important to prevent further stroke episodes [64].

Plantar Pressure Assessment

Other applications of gait analysis include the monitoring and assessment of plantar pressure distribution patterns, the identification and rectification of pathologic PPD patterns is important to prevent skin injury, or foot injuries.

- Wafai et al. presented a methodology to quantify the asymmetry of plantar pressure loading on both feet to diagnose foot pathologies. The load is quantified in different zones of the foot, and depending on the load asymmetry patterns, a specific foot diagnose can be done [56].

- Craig Bennetts et al. presented a clinical study on 800 patients with diabetic feet, and applied a k-means clustering algorithm to identify common PPD patterns. After the clustering model is built, new patients can be classified into the identified patterns. The identification of hyper-pressure zones on diabetic feet is very important, when the patients suffer of peripheric neuropathy, because patients can not feel the pressure on the feet, so when, extreme pressures are applied repeatedly, it can cause ulcers or even necrosis [71].

Fall Risk Assessment

Fall risk assessment is an important application for the quality of life of the elder community. On the review presented by Luis Montesinos [69], several inertial systems and gait analysis methodologies are reviewed, which aim to monitor, assess and predict potential fall risk for elder adults. Sensor footwear has also been used to assess fall risk, using gait activity detection methodologies based on GRF data.

Other applications

Many other applications can be found on the gait analysis literature, such as the research of walking strategies of different pathologies, for instance osteoarthritis [44]. Also, to reduce costs when developing systems for specific applications, sensor optimization can be done through gait analysis, by identifying and removing the sensors that do not contribute too much to the analysis [38]. Additionally, the assessment of orthotics can also be done, by quantifying the change that these produce on the natural gait pattern of the user [66]. Among many other applications can be studied and developed with gait analysis. During the last decade, the implementation of machine learning techniques has increased due to its high accuracy on classification tasks, such as individual recognition, or identification of pathological GRF patterns on gait [23], [72].

3.6 CONCLUSION OF THE CHAPTER

On this chapter, relevant literature regarding gait monitoring and analysis has been presented. First, a history of the gait monitoring and analysis was introduced (synthesized from Prof. Baker's article [19]). Then, a brief description and comparison of the main types of technologies used on gait analysis was presented. After stating our interest on wearable gait monitoring technologies, the state of the art of wearable sensors was presented, highlighting the contributions and limitations of the systems developed by the scientific community. Also, some real-life applications of gait analysis were described.

With the background presented on this chapter, the reader should be acquainted with some of the milestones and challenges on the field of GRF monitoring in gait with wearable systems, which will help the reader to understand the contributions of this thesis work.

CHAPTER 4:

DESIGN AND DEVELOPMENT OF SENSOR FOOTWEAR

4.1 INTRODUCTION

In this chapter, the design, development and characterization of a self-calibrating sensor footwear is presented. The chapter is divided into three main sections:

1. On the first section, considerations on design and development of a sensor insole to avoid mechanical noise on force sensors are presented.
2. Then, on the second section, the electronic specifications proposed for a smart sensor footwear are described, prioritizing the achievement of a robust, power-efficient, wireless transmission system, while maintaining a small-sized electronic board. Also, a self-calibrating algorithm and hardware were implemented to dynamically adjust the force measurement range (FMR) depending on the weight of the user, thus, improving the resolution of the force measurements.
3. Finally, the integration of the sensor footwear is described. Also, as far as we know, as it has not been reported on the sensor footwear literature, the importance of in-shoe characterization to achieve accurate plantar pressure distribution (PPD) measurements will be demonstrated, as high variability on the sensor response was found between sensors located on the same zones on left and right shoes. As well, high variability on the sensor response was found along the rearfoot, midfoot, and forefoot zones of the same shoe due to variations on the damping of the sole’s material.

4.2 SENSOR INSOLE

The sensor insole is the main component of a wearable PPD wearable system. Insole base material, and wiring considerations are to be made to prevent mechanical noise on force measurements. Thin, flat, cotton lining insoles were selected for sensor placing due to their low deformation and force damping. The chosen insoles, which are shown on Figure 4.1**,** had small perforations, which facilitated the arrangement of wiring trajectories. The design and development of a sensor insole is described below.

Figure 4.1. Cotton lining insoles used for sensor placement.

4.2.1 Sensor selection and positioning

Sensor selection and positioning are determined by the aim and expected reach of the designed system. For example, it is common that devices used on biomechanical research applications have high spatial resolution, as monitoring systems with large matrix of sensors are employed. On the other hand, on academic clinical studies, the implementation of insoles with discrete sensors along the foot are the most usual configuration. The critical zones for plantar pressure monitoring vary on some applications, however, heel, metatarsal and toe prevail on almost every sensor insole configuration.

To develop a general-purpose sensor footwear, force sensors were positioned on all common sensing zones found on discrete PPD monitoring literature: two heel zones, four metatarsal zones, and on toe; also, four extra force sensors were positioned on midfoot zones to cover effectively every zone of the foot. This design covers most of the specific zones also used on any PPD monitoring application found on gait analysis literature. The proposed sensor configuration is shown in Figure 4.2a, and the zones annotated in Figure 4.2b.

a)

Sensor N°	
1	Internal heel
2	External heel
3	External low medium foot
4	Internal low medium foot
5	Internal high medium foot
6	External high medium foot
7	Fifth metatarsal
8	Third metatarsal
9	Second metatarsal
10	First metatarsal
11	Hallux

b)

c)

Figure 4.2. Sensor selection and positioning

a) Eleven-sensor configuration for sensor insole.
b) Name of the zones where the sensors were positioned.
c) Flexiforce A301 sensor.

Sensor technology and brand naturally set a trade between cost and precision of the device. Force sensing resistors (FSRs) are an effective cost-precision solution in force measurement. FSRs change its resistance when an external force is applied on them, it is worth mentioning that the resistance change is non-linear. Non-linearity on the sensor response can be linearized through signal conditioning, which will be addressed later on this chapter. As for the force/pressure chosen sensor, the piezoresistive Flexiforce A301 (Figure 4.2c) sensor was selected.

The A301 sensor can endure approximately 445 N, which is enough to monitor a wide range of real-life activities on light and normal weighted individuals, and at least normal speed walks on heavy weighted. Once the sensor type and positioning were decided, the development of a sensing insole was planned.

4.2.2 Development of sensor insole

The sensor insoles were carefully handcrafted, the design was constantly improved on the process of development, as potential sources of noise were detected.

The methodology to build the sensor insoles is described below:

First, the sensors were positioned on the insole, on the proposed zones shown in Figure 4.3**.**

Figure 4.3. Sensors positioned on the cotton insole.

Then, the trajectories of the wires were planned with the following considerations:

- One pin of every sensor must be connected to a common wire.
- The wires must not pass below the sensing zones.
- The wires must not cross above or below other wires.

These considerations allow avoiding mechanical noise caused by raised edges due to wire bulging. On the planned wiring trajectories, ducts to rest the wiring were carved on the insole. The wires resting on the carved planned trajectories are shown in Figure 4.4**.**

Figure 4.4. Wires resting on carved ducts on the insole.

Afterwards, the sensors were soldered, and anti-impact rubbers were placed on the sensor areas. These rubbers have the exact area as the sensor, allowing to focalize the applied load on the sensor. Next, an acetate sheet was cutted and foot-shaped to fit on the insole, small circled-cuts on the sensor positions resulted on an acetate cover resting on the insole, only standing out the rubbers. The acetate cover avoids direct contact between the wires and the foot, which experimentally was observed to cause significant noise on the sensor signals.

Figure 4.5. Wiring of sensor insole

Finally, a thin fabric was sewed to the sensor insole, which harmonized the appearance of the insole to the shoe. Also, a 12-pin connector was soldered to the wires to connect to an electronic board. The final result is shown in Figure 4.6**.**

Figure 4.6. Final state of sensor insole

With this methodology, three pairs of sensor insoles were built. The insoles were on sizes 4, 5 and 7 (Mexican footwear scale). The variety of sensor insole sizing allows covering a larger population on both men and women. The sensor insoles connect through a 12-pin connector to an electronic board, which design will be detailed below.

4.3 ELECTRONICS

An electronic board was designed and built for each shoe. The board allows the device to operate on two modes, which are intended for different situations. The main tasks of the board are the acquisition of the voltage data of the sensors and the wireless transmission of the acquired data to the PPD monitoring software. On this section, design and functionalities of the smart sensor footwear are described.

4.3.1 Specifications of electronic system

The essential tasks of the circuit are: signal conditioning, voltage data acquisition, and wireless transmission. Such tasks, result on a large number of possible solutions, of which, some of them can interfere with other design considerations, for example: the size of the electronic board, which is best to maintain as small as possible to avoid interference with the gait naturality. Considering that, a scheme for the designed circuit was proposed (Figure 4.7), this scheme would allow the smart sensor footwear wirelessly transmit the data, or store it locally.

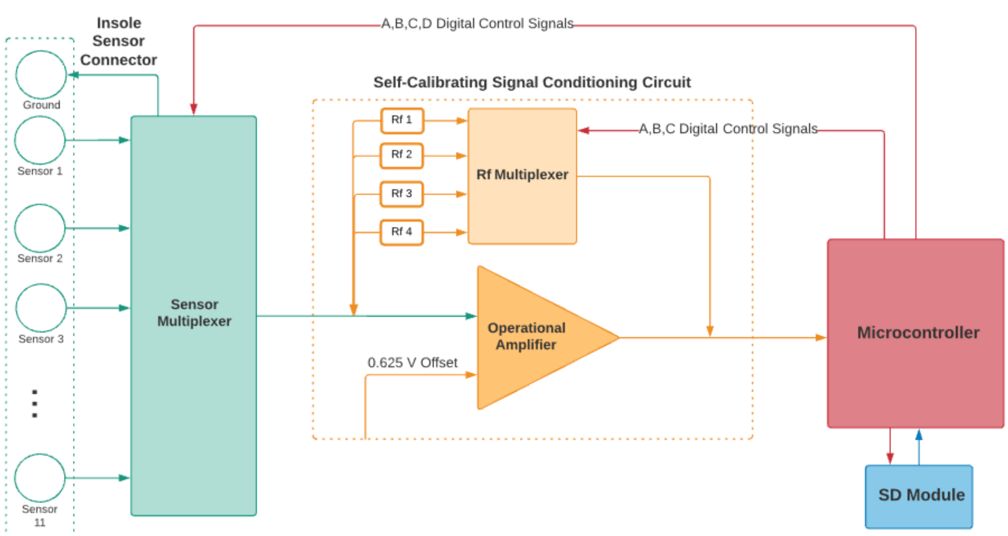


Figure 4.7. Circuit scheme of the proposed electronic board.

Starting from the left, the data flow was proposed as follows: Through the sensor insole connector, the sensor signals are connected to a 16-1 CD74HC4067 (Texas Instruments, USA) analog multiplexer, a microcontroller switches the control inputs of the multiplexer, connecting each sensor at a time to a non-inverted amplifier, which output is connected to an ADC of the microcontroller. A dynamic self-calibrating signal conditioning circuit was proposed for the circuit, the proposed circuit is based on an operational amplifier non-inverted amplifier configuration, which will be detailed on its own section of this chapter. Finally, when the signal is conditioned, the signal would be acquired by the microcontroller, and then either sent the data wirelessly to the PPD monitoring software, or store it locally on a micro SD memory. The selection of the microcontroller and transmitter is the key to achieve a small-sized, robust, power-efficient circuit.

4.3.2 Microcontroller and wireless transmitter selection

There are many combinations of microcontrollers and transmitters to achieve the task in hand; during preliminary experiments, a smart sensor footwear circuit was built, a PIC18F2550 and a XBEE radiofrequency module were employed to monitor real-time PPD. A robust 20m network was accomplished, even through walls, however, due to slow transmission speed, real time visualization of PPD was not achieved. Also, to create such a strong signal, the consuming power of the device was high; as power efficiency of smart sensors is an important feature, other transmitters were proposed. For this iteration, Bluetooth low energy (BLE) and Wi-Fi transmitters were prioritized. First, the ESP32 microcontroller (Espressif Systems, China) was tested, and then implemented. The low power consumption of the ESP32, the Bluetooth Low Energy and Wi-Fi capabilities make the chip a good alternative for the development of low-cost Internet of Things smart sensors.

Figure 4.8. ESP32 microcontroller.

The ESP32 is a very versatile microcontroller, as it can also transmit on both BLE and Wi-Fi. With this in mind, two operating modes were proposed for the smart sensor footwear:

- Indoor real time PPD monitoring with a wireless local area network, intended for consulting and rehabilitation rooms.
- Outdoor datalogger mode to record and store real-life activities, and then transmit them to a database.

The ESP32 has a 12-bit analog-digital converter (ADC), which was used for sensor data acquisition. A 12-bit ADC is enough to measure load changes during gait on the A301 sensor. However, the force applied to the sensor affects its resistance, thus, to acquire the data of the sensor, this resistance changes must be converted to a voltage signal that the microcontroller's ADC can read. On the next section, a signal conditioning circuit is detailed. The signal conditioning circuit was used to reduce the sensor´s non-linearity. To achieve even better accuracy on force measurements, on the next section as well, the development of a self-calibrating circuit will be presented, which would allow optimizing the PPD acquisition for every individual, independently of their weight.

4.3.3 Self-calibrating circuit: Signal conditioning

As for PPD monitoring systems, the force/pressure resolution varies between individuals. A fixed force measurement range (FMR) does not adjust optimally to all users, which vary in weight and consequently on the magnitude of the ground reaction forces applied on the shoe. Typical FMR on sensor footwear systems are 0 N - 200 N, which cover most of the potential users, however, we have found that individuals may apply a maximum of 25 N on any sensor during real-life walks, in which case, the measurements would lie on the 12.5 % of the FMR, and therefore limited resolution would be obtained on light-weighted individual measurements. A dynamical self-calibrating FMR algorithm was designed; the algorithm allows adjusting the FMR of FSRs depending on the maximum force applied by the user. Four FMR were proposed: 0 N - 25 N, 0 N – 50 N, 0 N - 100 N and 0 N – 200 N. The dynamical range was accomplished by a modification on a non-inverted operational amplifier signal conditioning circuit configuration (Figure 4.7), an extensive sensor characterization and a logic decision-making program on the software of the monitoring system.

First, the behavior of an A301 sensor was characterized from 0 N to 200 N inside a shoe on the heel zone. Then, using the force-voltage characterization data, the sensor's resistance behavior was obtained and fitted into the expresion shown on Equation 1:

$$\mathrm{Rs} = \begin{cases} 30\mathrm{x}10^{6}\mathrm{e}^{-0.18\mathrm{F_s}} & \text{when} \quad 0\ \mathrm{N} \leq \mathrm{Fs} < 20\ \mathrm{N} \\ -3.5\mathrm{F_s^3} + 802.6\mathrm{F_s^2} - 62339.9\mathrm{F_s^1} + 1793164.7 & \text{when} \quad 20\ \mathrm{N} \leq \mathrm{Fs} < 90\ \mathrm{N} \\ -0.05\mathrm{F_s^3} + 24.5\mathrm{F_s^2} - 4558.7\mathrm{F_s^1} + 341460 & \text{when} \quad 90\ \mathrm{N} \leq \mathrm{Fs} \leq 200\ \mathrm{N} \end{cases} \tag{1}$$

where *Fs* is the applied force on the sensor. Although, the resistance change is non-linear, it can be linearized with a non-inverted operational amplifier configuration. The circuit´s output voltage equation can be written as:

$$\mathrm{V_O} = \mathrm{V_{in}}(1 + \frac{\mathrm{R_f}}{\mathrm{R_s}}) \ , \tag{2}$$

where V_{in} is an offset for the voltage signal, R_s is the sensor´s resistance, and R_f is the feedback resistor which serves as the amplifier of the sensor’s signal. When R_f is modified, the voltage-force range is modified as well; therefore, the voltage-force range must be adjusted to the maximum forces applied by the target PPD groups and the characteristics of the acquisition subsystem. For instance, the signals were acquired with a 12-bit ADC from 0 to 3.3 V with a V_{in} offset of 0.625 V, and then the linearized signal outputs can be modeled as:

$$\mathrm{V_O} = \frac{(\mathrm{V_{max}} - \mathrm{V_{in}})}{(\mathrm{F_{max}} - \mathrm{F_{min}})}(\mathrm{F_s} - \mathrm{F_{min}}) + \mathrm{V_{in}} \quad . \tag{3}$$

On both equations, 2 and 3, the V_o can be maximized for a specific FMR (25, 50, 100, 200 N), which allows the equations to be equalized, and hence, R_f can be obtained (note that the F_{min} of the FMR is 0):

$$\mathrm{R_f} = \frac{(\mathrm{V_{max}} - \mathrm{V_{in}})}{(\mathrm{F_{max}}\mathrm{V_{in}})}\left(\mathrm{F_{max}}\mathrm{R_{s\_max}}\right), \tag{4}$$

$$\mathrm{R_f} = \frac{(\mathrm{V_{max}} - \mathrm{V_{in}})}{\mathrm{V_{in}}}\mathrm{R_{s\_max}} \ . \tag{5}$$

In Table 4.1, the optimal values of R_f were calculated for the four FMR of the A301 sensor.

Table 4.1

Theoretical optimal RF for non-inverted amplifier

Force Measurement Range (N)	Feedback Resistor (Ω)
0 – 25 N	4.1 MΩ
0 – 50 N	1.4 MΩ
0 – 100 N	511 KΩ
0 – 200 N	240 KΩ

Theoretically, for a sensor with similar signal response, applying the maximum force on the FMR (25, 50, 100, 200 N) would output a voltage of 3.3 V on the non-inverted amplifier signal conditioning circuit with its corresponding R_f. Before sensor characterization, an experiment was conducted to assess that every sensor would output approximately 4095 12-ADC units (3.3 V) when the maximum forces of the FMRs were applied. The forces were applied by a calibrated INSTRON 3369 universal testing machine. On Figure 4.9a, the voltage response of the eleven sensors of the left sensor shoe is shown, the theoretical optimal feedback resistor of 240 KΩ of the 200 N FMR was used, and the maximum force of 200 N was applied to every sensor. High variability is observed on the sensor responses on Figure 4.9a. As all the sensors are the same model and came from the same batch, similar responses are expected, however this variability led us to conclude that the position of the sensor on the sole is a source of variability, even if it is a flattened-sole footwear. Also, on Figure 4.9a can be observed that using the theoretical optimal R_f calculated for the sensor 2, sensor 2 indeed reaches 3.3V (4095 ADC units), however, sensors 4, 7, and 9 surpass the 3.3V threshold, which means that the ADC is saturated, and hence, PPD data would be lost. A solution could be to implement a specific conditioning circuit with their specific FMR R_{fs} for each sensor to take advantage of the full voltage range, however this would over complicate the circuit increasing the size of the electronics. Which is unacceptable, due to the gait naturality loss caused by bulky electronics on footwear systems or strapped on electronics.

The approach taken was to select a single R_f for each FMR for each shoe, that is, for the proposed system, four R_{fs} for each shoe. The selected R_f was decided by observing the most sensible sensor for each FMR, that is, the one/ones that would output 3.3 V at the

F_{max} of the FMR; the other sensor responses would lie below the 3.3 V ADC limit. The chosen R_{fs} are shown on table 4.2.

Table 4.2

Experimental optimal Rf for non-inverted amplifier

Force Measurement Range (N)	Feedback Resistor (Ω)
0 – 25 N	3.3 MΩ
0 – 50 N	1 MΩ
0 – 100 N	470 KΩ
0 – 200 N	220 KΩ

The experiment to obtain the Figure 4.9a results was repeated, but, this time the experimental optimal 0-200 FMR R_f was used. The results are shown in Figure 4.9b. It can be observed, that sensors 5, 7, and 9 reach the 3.3 V threshold, and the other sensor responses lie below the limit, this allows optimizing resolution for the proposed signal conditioning circuit, with few low cost components.

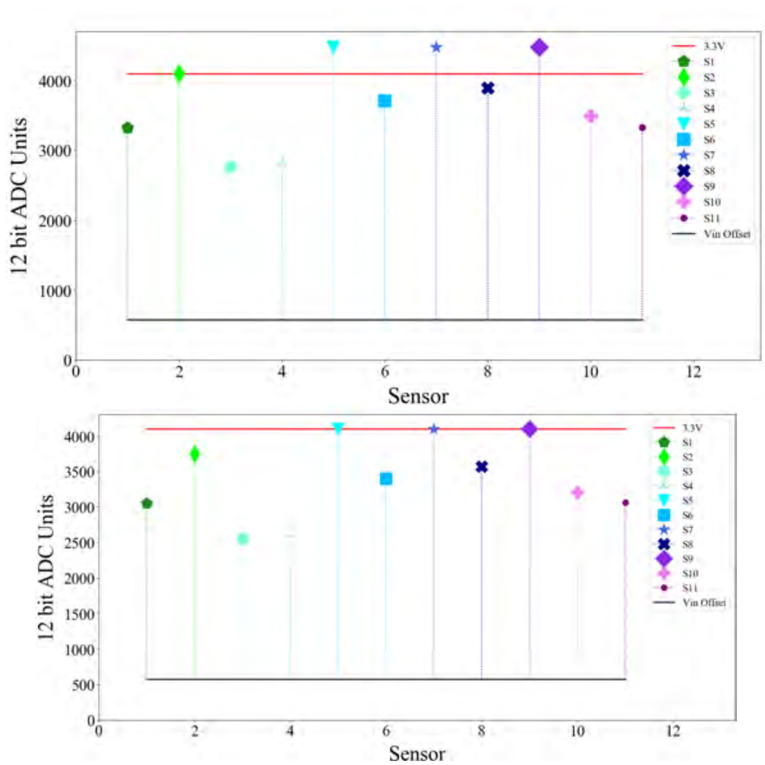


Figure. 4.9. Voltage response of the sensor with 0-200 FMR R_f
a) Sensor response to 200 N and theoretical optimal 200 FMR R_f ;
b) Sensors response to 200 N and experimental optimal 0-200 FMR R_f.

Once the R_f values were obtained, a multiplexer was integrated to the signal conditioning circuit. The control inputs of the multiplexer were connected to the ESP32 microcontroller. At the analog inputs of the multiplexer, the R_{fs} were connected, and on the other terminal of the R_{fs}, the R_s (sensor) was connected as shown on the self-calibration signal conditioning circuit in Figure 4.10. Finally, the analog output of the multiplexer was connected to the voltage output of the operational amplifier, closing the feedback. The described modification on the signal conditioning circuit allows the system to optimally adapt the FMR for each user. The FMR adaptation is achieved through a self-calibration phase, in which the sensor footwear starts sensing at the maximum FMR, for instance 0-200 N, on this phase, the user walks at normal speed on a clear hallway, during the walk, the maximum force applied by the user is detected, then, through a logic decision making program, the optimal FMR for the user is selected and the microcontroller switches the R_f to complete the FMR adjustment. The usage of the optimal FMR improves the resolution on GRF measurements, as personalized force-voltage ranges adapt to the ADC span, which may help to take advantage of the sensor sensitivity on the required FMR.

4.3.4 Design of electronic board

Once all the specifications of the circuit were defined, the design of an electronic board was made. An advantage of using the ESP32 microcontroller, is that the transmitter is also contained in the chip, which saves more space, and allows developing small circuit boards. The circuit design proposed for a smart sensor footwear is shown in Figure 4.10.

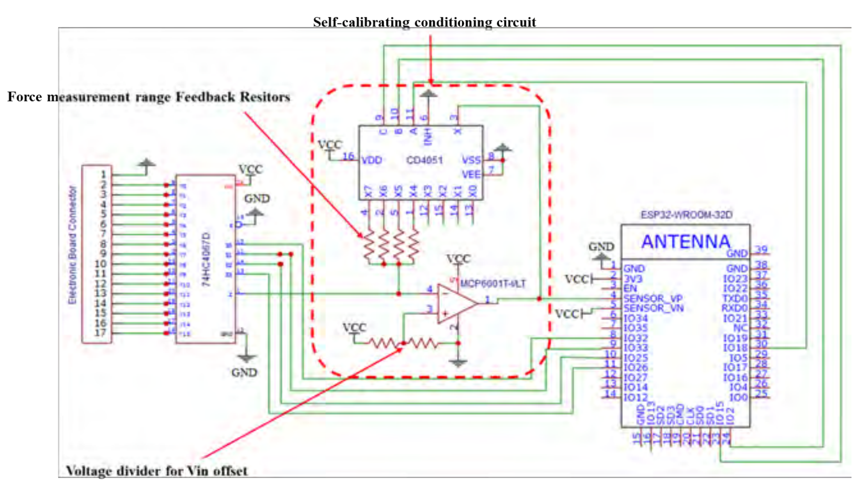


Figure 4.10. Smart sensor footwear circuit.

The circuit is integrated by a low number of low-cost components. First, the FMR would be automatically selected through a self-calibrating process which will be detailed on Chapter 5. The microcontroller uses 4 digital outputs to switch the 16-1 analog multiplexer to acquire, one by one, the eleven sensor signals incoming from the sensor insole. The selected sensor signal enters the signal conditioning circuit, then it is amplified depending on the selected FMR. Through the ESP32's 12-bit ADC, the voltage signals are acquired, resulting on the conversion of a 0 V – 3.3 V, to a 0 – 4095 ADC unit range. The eleven ADC signal values, then would be sent to a PPD monitoring software. Both, sensor footwear software and monitoring software development will be detailed on Chapter 5.

4.4 DEVELOPMENT AND CHARACTERIZATION OF SENSOR FOOTWEAR

The development and characterization process of a sensor footwear is described on this section. Considerations on the development of a sensor footwear are presented, these considerations would help to avoid mechanical noise on the force measurements, and on the characterization process of the sensor footwear. Also, as far as we know, as it has not been reported on the sensor footwear literature, the importance of in-shoe characterization to achieve accurate PPD measurements will be demonstrated, as high variability on the sensor response was found between sensors located on the same zones on left and right shoes. As well, high variability on the sensor response was found along the rearfoot, midfoot, and forefoot zones of the same shoe due to variations on the damping of the sole's material.

4.4.1 Sensor footwear integration

Considerations on the selection of the recipient footwear for the sensor insoles are as important as good sensing setups. The most important considerations are described below:

1. The sole of the footwear must be flat, as different heights or sole reliefs would modify the natural PPD. The importance of flattened-sole footwear lies on the standardization of the tests recorded on the sensor footwear. If tests are recorded

on different sole styles, the PPD is modified for each user, leaving no chance for objective comparison between the recorded tests.

2. The footwear shall allow to be half-opened and closed back. This feature would permit an in-shoe characterization, which improves significantly the accuracy on force measurements.
3. The device must be all-in-shoe, that is to say, that no strapped-on electronics are allowed, as it modifies the natural gait. Electronics should be kept in some way in/on the shoe, on this sensor footwear, a sewed pocket is proposed.
4. The aesthetics of the sensor footwear. It is not quite an important feature in matters of performance, even less if the device is only used on consulting and rehabilitation rooms, however, if the system is intended to be used on real life activities, social acceptance of the sensor footwear takes an important role on the success of the implementation of these type of wearable systems.

Footwear were selected to allocate the sensor insoles. To assure natural PPD, flattened-sole footwear was selected. Fabric non-laced footwear are good alternatives as they can be half-opened and sewed to be closed afterwards. Once, the footwear was selected, in-shoe sensor characterization was planned. Shoe modifications were made. First, the insoles of the footwear were removed, and replaced with the sensor insoles. Then the shoe was sliced on the instep, which would allow the press to reach every sensor on the sensor insole.

4.4.2 Sensor footwear characterization

Sensor characterization consists on the obtention of the behavior curve of the sensors, which is the relationship between the output variable of each sensor connected to the signal conditioning circuit (Voltage), and the input variable applied to the sensor (Force). In other words, these characterization curves allow accurate estimation of the force that was applied to the sensor according to the acquired voltage for each sensor.

The accuracy and reliability of the force measurements depends on good sensor characterization. For example, on preliminary experiments, characterization was made on the sensor insole outside the shoe, when the evaluation phase was finished, it was concluded that not only every footwear modifies, as it is obvious, the PPD of the user, but also the sensor response to the applied force, which results on significative errors on the magnitude of the estimated force. The sensor response change could be caused due to the different force damping of the footwear’s sole. Therefore, in-shoe sensor characterization would allow obtaining reliable force measurements.

In-shoe sensor characterization was made on a certified INSTRON 3369 universal testing machine on the “Laboratory of Optical and Mechanical Tests” at CIO, León, Gto., México. The characterization setup is shown in Figure 4.11. An accessory with the same sensing area as the sensor was attached on the press to focus the force on the sensor as shown in Figure 4.11a; as the footwear was half-opened, the press can reach every sensor. On Figure 4.11b, the main window of the INSTRON machine is shown, at the top left zone of the screen the applied force is displayed. To obtain the voltage of the sensors, a TCP socket program was used, in which one could send a command to the ESP32, to set the desired FMR for characterization, and to acquire and transmit the actual voltage data.

Figure 4.11. Footwear sensor characterization setup
a) Half-opened footwear for in-shoe characterization on INSTRON 3369;
b) INSTRON 3369 graphical interface.

Four FMR were proposed for the self-calibrating algorithm: 0 N – 25 N, 0 N – 50 N, 0 N – 100 N, 0 N – 200 N, which means that, for every sensor, four curves were obtained with their respective R_f. For the 25 N and 50 N ranges, 6 and 11 measurements with 5 N jumps were made respectively. Also, for the 100 and 200 N ranges, 11 and 21 measurements with 10 N jumps were made.

Calibration sheets were made for each shoe. On Figure 4.12, the characterized sensor´s behavior of the left footwear for the 0 - 200 N FMR is shown. It is observed on Figure 4.12, that sensors behave differently across the shoe, the inconsistences on sensor response are possibly caused by variable damping across the footwear sole material, even on flattened-sole footwear.

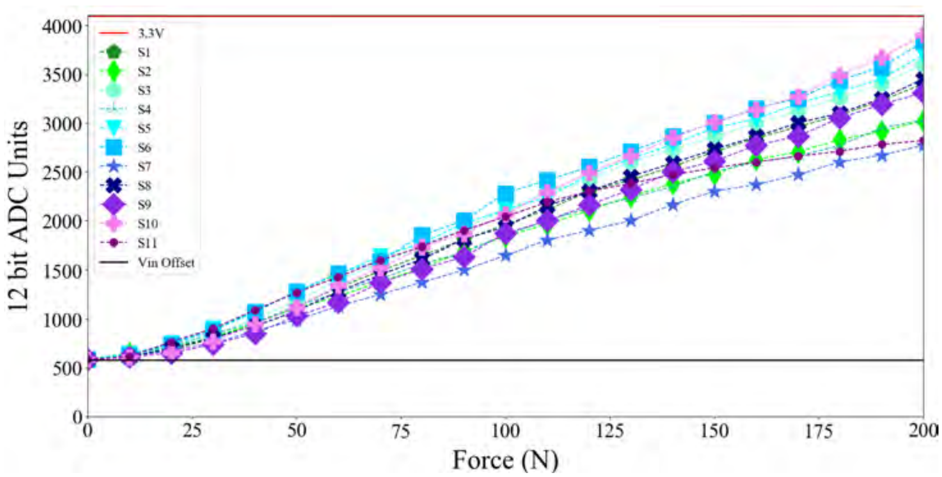


Figure 4.12. Different response of the sensors when the same force is applied, in the same shoe.

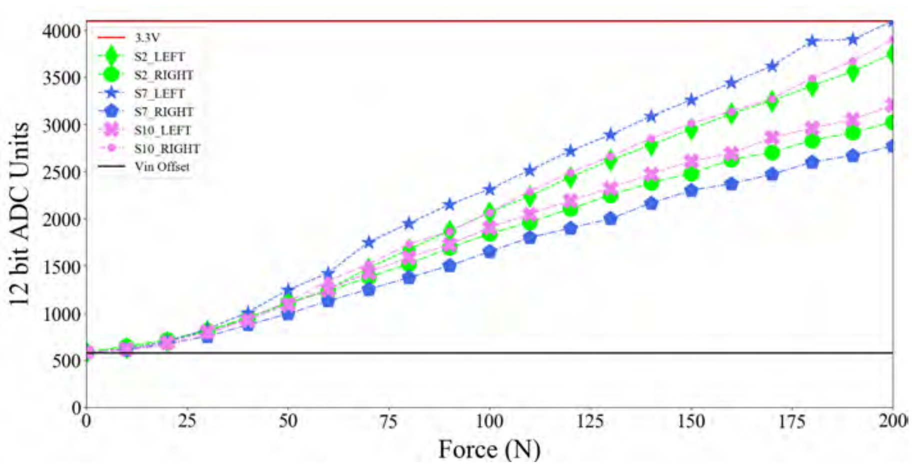


Figure 4.13. Variation in sensor response when the same force is applied to three sensors on the same position on different shoes.

In Figure 4.13, the response of three sensors between left and right footwear is compared. The sensors compared in Figure 4.13 are on the same position on different shoes, all 3 sensors (sensor 2 – heel, sensor 7 – first metatarsal, sensor 10 – fifth metatarsal) present a notable variation on response even if they are in the same position on the left or right shoe. This variability demonstrates that every shoe affects significantly on the GRF measurements. That said, when generic sensor curve adjustment, or an out-of-shoe characterization is used, leads inevitably to random and unreliable inter-subject GRF measurements. Specific FMR R_{fs} along with in-shoe characterization enhances resolution and accuracy on GRF measurements.

It is also observed that between left and right shoes, the sensor behavior changes, which demonstrates the noise that can be caused due to the variability of the damping of the sole's material, even on flattened-soled footwear. Not to mention that using non-specific insoles for its own shoe, would cause also noise due to the alterations of the natural PPD due to the sole's relief. Monitoring PPD with non-shoe specific insole in-shoe characterization would result on the impossibility of objective PPD comparison between subjects. In-shoe characterization along with self-calibration provide a monitoring system accuracy enhancement by improving resolution through the selection of the optimal FMR for every user. Also, the standardization of flattened-sole footwear would allow to compare objectively PPD measurements between subjects.

Finally, when characterization was finished, the footwear was sewed again. As wearable in-shoe systems have been reviewed, a device that does not affect gait naturality is essential to obtain the characteristic PPD of the individual. Bulky electronics and strapped-on electronics are some of the principal gait-naturality affectations. Aesthetics and comfort of the device are also to be considered for a real-life gait monitoring application, as social acceptance may not contribute to the device performance, but the viability of the deployment of these systems on ambulatory and real-life applications is affected. The final stage of one of the sensor footwear pairs is shown in Figure 4.14.

Figure 4.14. Sensor footwear.

4.5 CONCLUSION OF THE CHAPTER

The design and development of the hardware for a PPD monitoring system was presented. Sensor footwear was designed, developed, and characterized. Sensor insole considerations on design and development were described to avoid mechanical noise on the sensors. The importance of in-shoe sensor characterization was presented, as high variations on the sensor response were found between shoes and even along the same shoe. A dynamical self-calibrating algorithm was proposed, in which the sensor footwear detects the maximum applied force by the user with a calibration FMR, then, by a logic-decision program the feedback resistor of a non-inverted amplifier signal conditioning circuit is switched to adjust the FMR optimally to the weight of the user, and thus maximizing the resolution of GRF measurements for every individual. Four characterization curves were obtained for each sensor (one for each proposed FMR), shoe-specific characterization sheets were made, which would be integrated to a PPD monitoring system. The communication protocols and the development of the PPD monitoring software will be detailed in the next chapter.

CHAPTER 5:

DESIGN AND DEVELOPMENT OF GAIT MONITORING SOFTWARE

5.1 INTRODUCTION

In this chapter, the development of software tools to monitor gait is described.

First, two communication setups are described. Each setup is intended to operate in different environments, for example, indoors to monitor gait in consulting or rehabilitation rooms (using a PC), or outdoors for ambulatory monitoring applications (using a smartphone). The network mode of the sensor footwear can be switched effortless using a smartphone application, which makes the device versatile and easy to use both inside the lab and on real-life applications.

Then, the design of the microcontroller´s program of the sensor footwear is presented. The program is divided into two main sections: the initialization and setup of the program, and the main loop. The operation of the program, functions and dataflow are described.

After the sensor footwear´s program is explained, the development of two graphical user interfaces (PC and mobile) are presented. These interfaces interact with the sensor footwear, providing easy to use monitoring tools for any user. The features and dataflow of the software are described.

5.2 NETWORK SETUPS OF THE SYSTEM

Before the development of the gait monitoring software, network setups were proposed. In this section, two network setups are presented: a wireless local area network for indoor gait monitoring, and a point to point network setup for outdoor applications. The configurations of both server and clients for these setups are highlighted.

5.2.1 Wireless Local Area Network

Gait laboratories, consulting and rehabilitation rooms are the most likely places where the developed gait monitoring system could operate. As the systems on these places are mostly fixed, we proposed a wireless local area network to communicate the sensor footwear to the monitoring software. The network setup is shown in Figure 5.1.

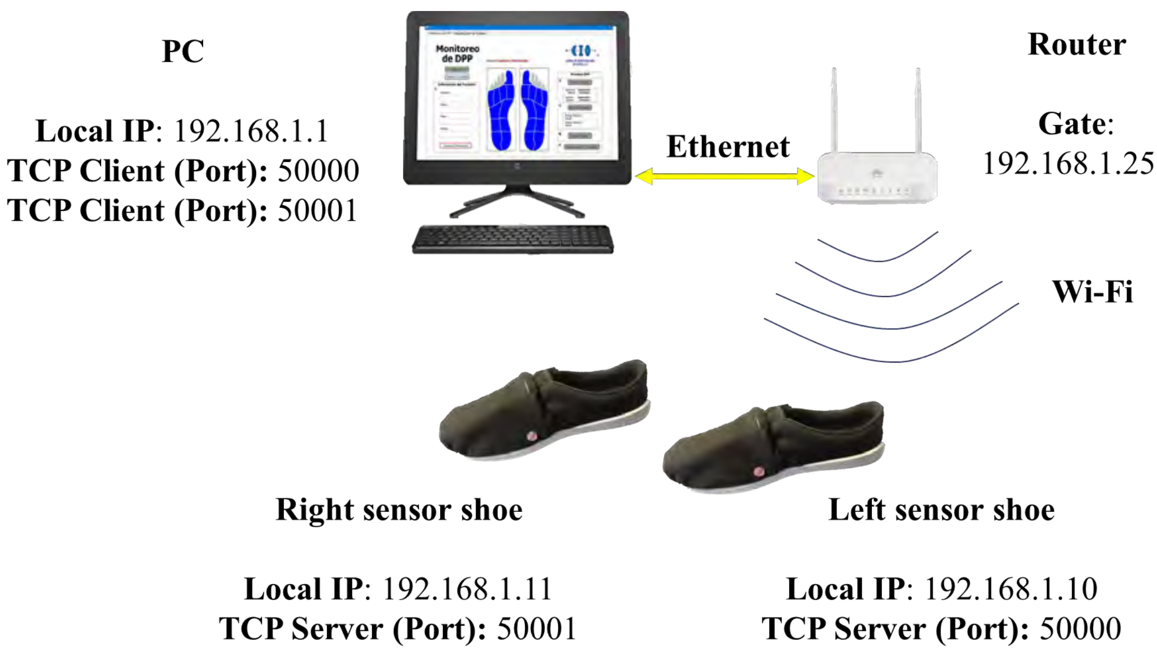


Figure 5.1. WLAN's setup.

A router is deployed to create a WLAN. The computer may connect to the network wirelessly, however, for the real time visualization mode, an ethernet connection is recommended, as the communication is smoother. The sensor footwear connects to the network through the ESP32 2.4 GHz antenna, the network´s SSID and password are stored in the SD card memory of the sensor footwear.

A TCP/IP protocol is implemented to communicate the sensor footwear with the PC. Each sensor shoe set ups a TCP socket server in a dynamic port (ports between 49152 to 65535). On the PC's end, two TCP clients are implemented (one for each sensor shoe). The requirements to connect to the TCP socket are: being connected to the same network as the server, and the IP address and port of the socket server. Once the client connects to the socket, a bidirectional communication channel is enabled. Then, the client may send strings (character arrays) containing commands for the sensor footwear to execute. The sensor footwear should always send a response to the client, either containing the requested data (i.e. shoe ID code, sensor data, etc.) or a confirmation of the reception and execution of the command (force measurement range adjustment, start/stop recording).

This setup enables a robust network for indoor applications, such as the assessment of gait in consulting or rehabilitation rooms, or the research of gait through clinical studies in controlled environments. The distance covered by this network is determined by the power of the router, and the interference of walls or other solid objects.
This setup was proposed for the PC's software real time visualization mode, however, if real time visualization is not relevant to the application, a developed smartphone app (Section 5.5) can be used as well with this setup to record gait tests. The limitation of this setup is that the sensor footwear must always be on the router's range, which limits its use to indoor applications. However, a second network setup is proposed for out-of-the-lab applications.

5.2.2 Point to point network

For applications that require gait monitoring during real-life activities such as fall-risk assessment, a point-to point network using Bluetooth is proposed to communicate each sensor shoe to a smartphone (Figure 5.2). The purpose intended for this network is to create a portable gait monitoring setup, in which the smartphone acts like a "remote control" of the sensor footwear, the user would use the smartphone app to calibrate the sensor footwear, start or stop recording the sensor data, and synchronize the recorded tests on a cloud database.

Figure 5.2. Point to Point network setup.

Now that the network setups have been presented, the sensor footwear program is presented in the following section.

5.3 SENSOR FOOTWEAR PROGRAM

The sensor footwear´s control unit is the ESP32, it can be programmed with C++, Micropython, or Lua. The programming language used for this prototype is C++. The program can be separated into two sections: the initialization sequence, where the global variables are defined and the ESP32 connects to the desired network setup, and the main loop, in which the program handles the commands sent by the user´s interface (PC or smartphone).

In the following subsections, the description of the functions of the sensor footwear, and how the data flows through them, is presented. Starting of course, at the initialization of the device.

5.3.1 Initialization

At the initialization of the program, the following sequence is executed (Figure 5.3):

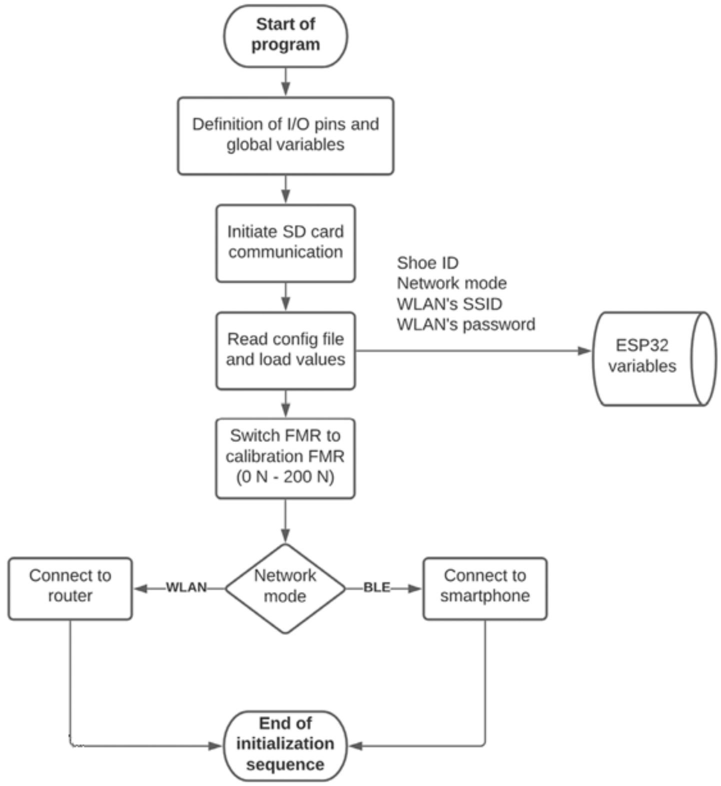


Figure 5.3. Initialization sequence.

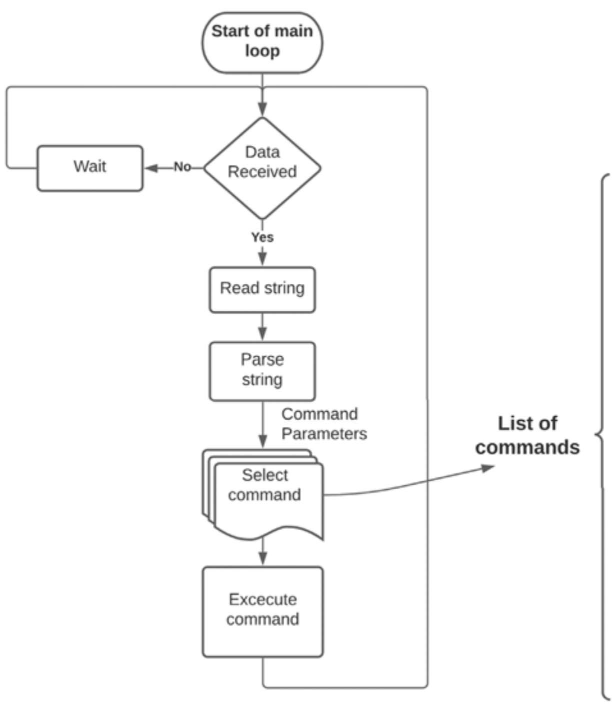
1. First, the input and output pins of the microcontroller, and global variables of the program are defined. These definitions set up the modules of the device, such as the analog to digital converter (ADC), the SD memory card, and timers, to operate correctly.
2. After the definition of the pins and variables, the communication of the microcontroller to the SD module is initiated, and a configuration file is read. The configuration file contains the default values of the device, such as the shoe identification code, the network mode, and the id of the WLAN network and its access password. The shoe identification code is unique for every shoe, for instance: "L4_v1" and "R4_v1", where L and R stand for left and right (shoe) respectively, the number to the side of the L (or R) represents the size of the shoe (Mexican size), then, the underscore is a separator, finally, v1 stands for version 1 of the prototype. This code is very important because its associated to an in-shoe-specific sensor calibration sheet, used to obtain accurate ground reaction forces (GRF) measurements.

3. After the configuration values are loaded, the self-calibration circuit switches the force measurement range (FMR) to the calibration FMR (maximum force FMR), in this case 0 – 200 N.
4. Finally, depending on the network mode value loaded in the configuration file, the sensor shoe tries to connect to the system's WLAN using the configuration values, or makes himself discoverable to other Bluetooth devices.

Then, the program enters to the main loop of the program, where it receives and handles the commands from the connected interface (PC or smartphone).

5.3.2 Main loop

Once the sensor shoe is connected to the router (WLAN), or paired and connected to a smartphone via Bluetooth, the main loop handles the data received through the 2.4 GHz antenna. In Figure 5.4, a flowchart of the main loop is shown.



Command	Parameters	Description
T	-	Send shoe id to client
B	-	Send battery percentage to client
R	Calibration level: 0, 1, 2 or 3	Switch FMR
Z	-	Return to calibration FMR (0 N - 200 N)
A	-	Acquire sensor data and send it to client
C	File name: "A0000"	Select SD file or create it if not existent
L	Timer interval: "20000" (in microseconds)	Define timer interval (sampling frequency)
S	-	Start/Stop recording sensor data on actual SD file
D	File name: "A0000"	Send file data to client

Figure 5.4. Main loop flowchart and list of commands of the sensor footwear program.

The incoming stream of data is read as a string. This string is parsed with the underscore (_) character as separator. Two fields must be separated from the received string:

command, and a parameter. The available commands for the sensor shoe are also shown in Figure 5.4. Once, a command is identified, it is executed, and a response is sent to the client. Then, the loop continues indefinitely, until the sensor shoe is turned off. The design of the program enables a versatile and easy to use smart sensor footwear. To interact with the sensor footwear, graphical interfaces were designed. In the following section, a PC gait monitoring software is described.

5.4 PC GAIT MONITORING SOFTWARE

The field of gait monitoring and analysis is vast, research groups have extensively studied the relation of gait to a large number of pathologies, not only related to the lower limb biomechanics, but also to neurological pathologies. To develop clinical studies, controlled indoor environments are mostly used to monitor the gait of the patients. For these applications, a PC gait monitoring software was designed.

The programming language used to develop the gait monitoring software is Python, the main reasons to choose this language are the multiplatform compatibility (Windows, OSX, Linux) and the ease of implementation of machine learning algorithms.

The design of the graphical interface was made using the Python library PyQt5. The main screen of the gait monitoring software is shown in Figure 5.5.

Figure 5.5. Gait monitoring software interface.

This tab shows the main feature of the software: plantar pressure distribution (PPD) monitoring during gait. In the following subsection the real time visualization mode of the system is presented.

5.4.1 Real time visualization mode

The real time visualization mode allows the user to observe and record the PPD during gait. The interface was designed to guide intuitively the user through the recording of the test sessions. The test recording follows the process described below, also, the internal loop of the software for the real time visualization routine is shown in Figure 5.6.

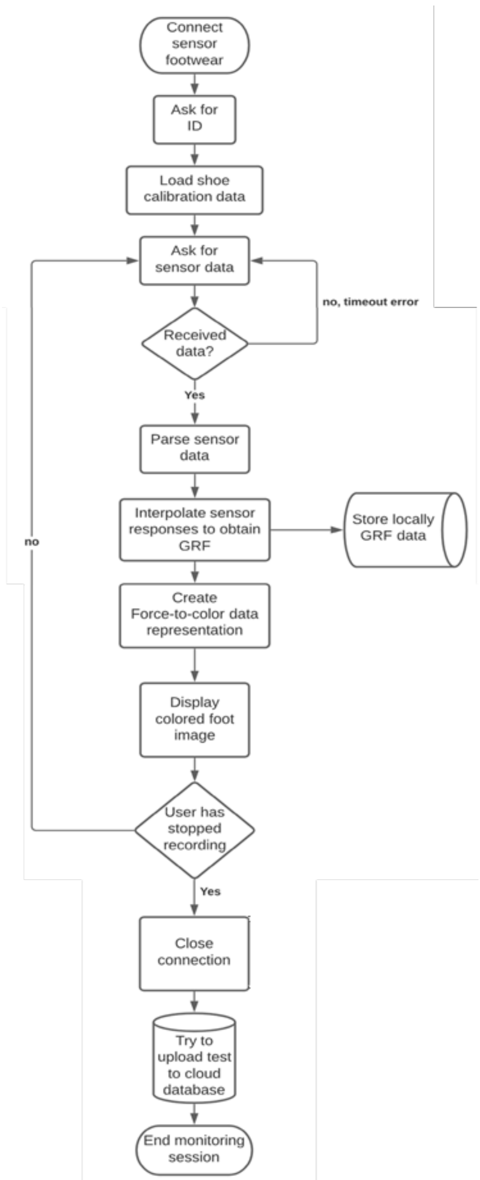


Figure 5.6. Real time visualization routine, flow chart.

1. First, patient data such as name, age, height and weight are captured.
2. Then, the software connects to the sensor footwear. The software handles each sensor shoe in separate processor threads, thus, achieving parallel and asynchronous communication.
3. Then, the footwear sends their identification codes, which are used to select the shoe-specific characterization sheets to obtain accurate GRF.
4. Afterwards, the self-calibration process is done as follows:
   a) On the gait monitoring´s software, the user presses the self-calibration button, the software commands the ESP32 microcontrollers to switch to the maximum force range available (0 N – 200 N).
   b) Then, the user shall walk a round trip on a clear corridor. As the microcontrollers constantly send GRF data, the software detects the maximum force applied on the shoes.
   c) Next, when the patient finishes the self-calibration round trip, the user commands the software to end the self-calibration process.
   d) Immediately, the software selects the optimal FMR depending on the maximum force applied during the self-calibration walk, and the software sends a command to the ESP32s to switch the multiplexer R_f to the corresponding FMR.
5. Then, the monitoring system is ready to record the gait with an optimal force range. When desired, the user can press the “record button” and instruct the patient to do the gait test.
6. Once the patient finishes the test, the user shall press the “record button” to stop the recording session.

As the system is still calibrated, several tests can be recorded following steps 5 and 6. However, if desired, the user can reset the calibration through the “restart button”, which returns every variable on both software and microcontrollers to their initial state.

Once the tests are recorded, they are automatically stored both locally on the PC and on a dropbox cloud database. If the computer does not have internet access at the time when the tests are recorded, it can manually synchronize the test database by clicking the backup button on the main tab of the interface. By clicking the button, first the PC compares the list of the local tests with a list on the dropbox storage, then, the PC uploads the tests that are not on the cloud, and downloads the ones that are not locally stored (for example, tests recorded and uploaded with the smartphone app).

If desired, the tests can be reproduced through the gait test reproduction feature of the software, which is described in the following subsection.

5.4.2 Gait test reproduction

Recorded tests can be reproduced using the local storage of patient records, which are organized by name, date and number of the test. Through the reproduction tab of the graphical interface, the user can select a specific test and play the file in two representations: foot colored images, or time-force graphs. The interface and setting of the gait test reproduction feature are shown in Figure 5.7

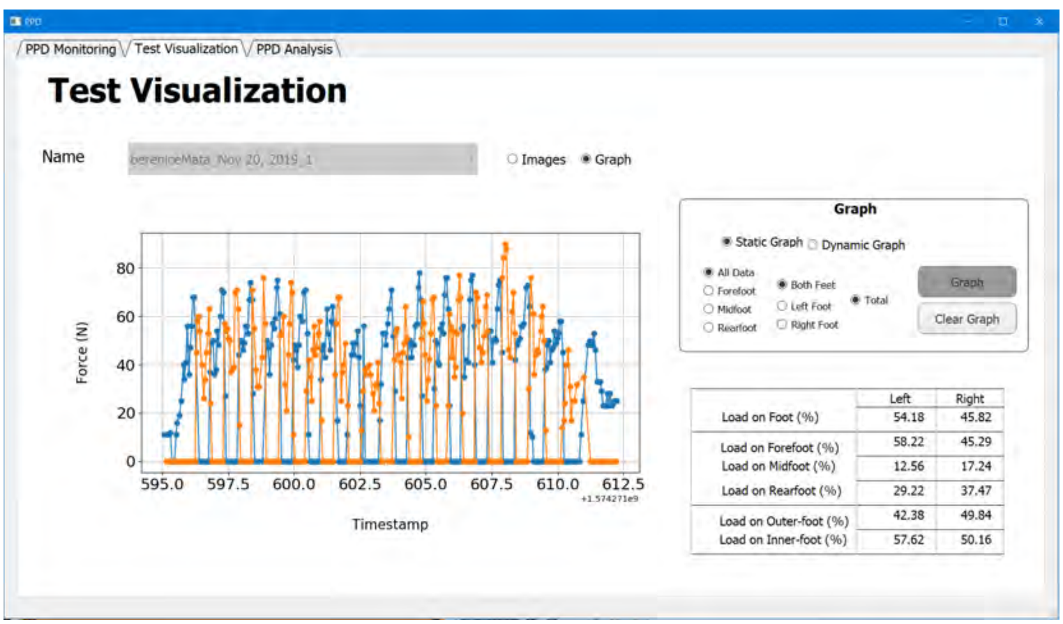


Figure 5.7. Gait test reproduction feature.

In Figure 5.7, the time-force graph of a gait test is shown. The graph can be static (all data shown at once), or dynamic, that is to say that the graph is shown imitating the real time visualization mode. For these graphs, the data shown can also be selected by the user, for example, the graph can show only the data of the left or right sensor shoe (or both). Also, the graph can show the data of each sensor, or the total ground reaction force (the sum of each sensor data), or sections of the data, such as the load of only the backfoot, midfoot or forefoot.

Furthermore, the force load percentages, for each foot and their sections are shown on a table at the side of the graphic. These table may help to observe if the patient walks with significant imbalance, or loads its weight abnormally towards a foot section.

Other features of the software include data preprocessing, which is described in chapter 6, gait analysis experiments are also described in chapter 6. In the following subsection, a smartphone app for gait monitoring is presented.

5.5 SMARTPHONE GAIT MONITORING APP

Nevertheless, not all gait monitoring and analysis applications need real time visualization, nor are developed inside-the-lab. The gait monitoring for fall risk assessment, energy expenditure quantification, among others need to monitor gait under real-life daily activities. For this purpose, a smartphone application was developed for Android operating systems using the Java programming language. The main screen of the app is shown in Figure 5.8.

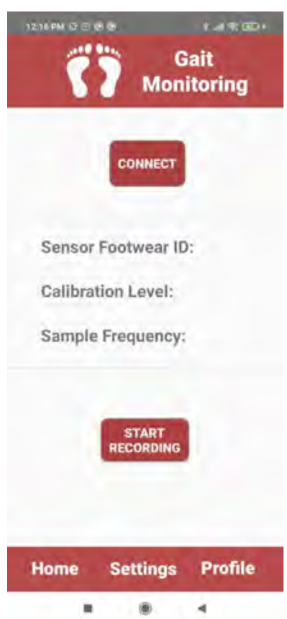


Figure 5.8. Main screen of Android app.

The app can work with both network setups, for example, if the gait is to be monitored at the home of the patient, the WLAN setup can be used. It is only needed that the sensor footwear and the smartphone are connected to the same network. However, when the user leaves its house to continue his daily activities, the point to point network can be used. Through the settings tab, the user can easily switch the network mode of the app.

This app works as a remote control of the sensor footwear, so to speak. The user can calibrate the sensor footwear, start or stop gait monitoring, and synchronize the recorded files to the cloud database, where the specialist may review the results for further analysis.

5.6 CONCLUSION OF THE CHAPTER

In this chapter, the design and development of software for gait monitoring has been presented. First, two network setups were proposed to communicate user interfaces to the developed sensor footwear. A WLAN network setup was proposed for indoor gait monitoring applications in gait labs, or consulting and rehabilitation rooms. Also, a point to point network was proposed for outside-the-lab gait applications.

Then, the design of the program of the microcontroller of the sensor footwear was presented, where the two sections of the program were described. First, the initialization routine of the microcontroller, in which the sensor footwear initializes the ADC, and SD memory modules, and connects to the selected network mode. And then, the main loop of the program, where the microcontroller handles and executes the commands of the user interfaces.

Afterwards, two developed software solutions were presented to interface the user with the sensor footwear. The first one, a PC monitoring software that was designed for real time visualization of the plantar pressure distribution during gait. And secondly, a smartphone application designed to monitor gait during real life activities.

CHAPTER 6:
GAIT ANALYSIS

6.1 INTRODUCTION

In this chapter, the main focus is to present the proposal and implementation of a methodology for gait test acquisition, and a preprocessing gait data pipeline for the gait monitoring and analysis system. Both the test acquisition methodology and the data pipeline were proposed to standardize the data acquisition and preprocessing for the analysis applications described on this thesis, and on our future work.

Also, a proof of concept about classification of ground reaction force (GRF) patterns during gait is demonstrated using the developed gait monitoring and analysis system. For this experiment, the natural GRF pattern of an individual was recorded, also two pathological GRF patterns were simulated by placing perturbations on the foot which generated repeatable GRF patterns. Then, the three patterns were preprocessed, converted to images and fed to a convolutional neural network to build a GRF gait pattern classification model.

6.2 DEVELOPMENT OF PREPROCESSING GAIT DATA PIPELINE

In this section, the development of a preprocessing gait data pipeline is described. The pipeline takes as inputs the raw signals recorded by the sensor footwear, segments the relevant steps and outputs standardized data frames, each one containing a single step. The preprocessing gait data pipeline was designed to work with gait data frames acquired with the following methodology.

6.2.1 Test acquisition methodology

A methodology to acquire repeatable gait samples with the developed sensor footwear is proposed. The tests are recorded on a corridor, the patients are instructed by the specialist to walk *n* round-trips at their natural walking speed, which may normally be between 1.18 m/s and 1.42 m/s. The test protocol is shown on the flow chart in Figure 6.1a, also, Figure 6.1b depicts graphically the test acquisition protocol.

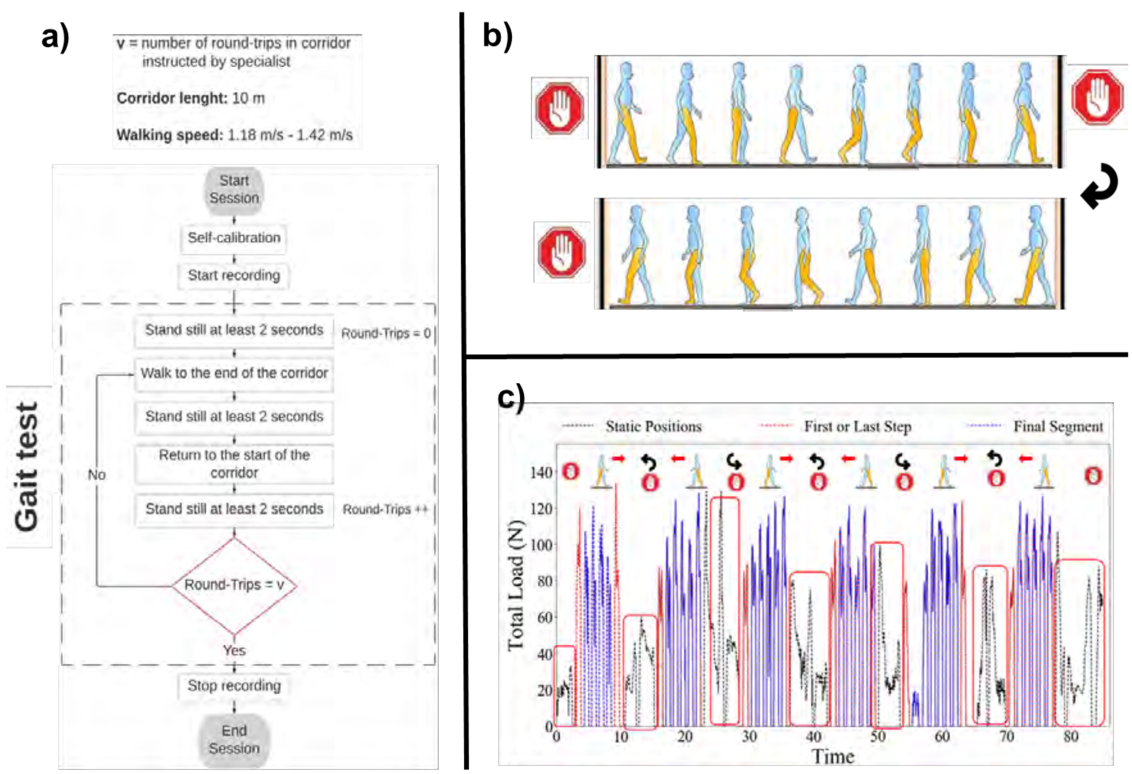


Figure 6.1.

a) Gait test flow chart. **b)** Gait test movement protocol
c) static positions flags (black signal inside red rectangles)

It can be noted, that pauses are instructed on the gait test protocol, the purpose of these pauses are to act as flags to detect and segment the gait relevant steps of the recorded tests.

In Figure 6.1c, the sum of the GRF of the left sensor shoe is shown, inside the red rectangles, the static positions and turns are highlighted. The process of using these flags to segment the data is described in the following section, in which the development of the preprocessing gait data pipeline is presented.

6.2.2 Preprocessing gait data pipeline

In this section, the development of a preprocessing data pipeline is described. It was developed to automatically segment the relevant data from tests acquired with the methodology proposed above. The purpose of the gait data pipeline is to automate the preprocessing of the tests, which saves time on manual slicing the data, and standardizes the signals of the relevant gait-cycles, generating ready to analyze data frames for GRF analysis applications.

The data pipeline is integrated by two algorithms, the first one is the gait-segmentation algorithm, it makes two cuts to output the characteristic gait cycles of the individual. The second, is the signal standardization algorithm, which detects the gait phases of the segments thrown by the gait-segmentation algorithm and outputs uniform data frames. The development of the former is described below.

6.2.2.1 Gait-segmentation algorithm

The algorithm takes as input the recorded tests which contain 22 raw signals (11 sensor signals from each sensor shoe) and their respective timestamps acquired during v round-trips along a clear corridor. Each round-trip is defined as a gait segment. Then, the algorithm slices the data to generate $2v$ gait segments. The resulting gait segments contain the characteristic PPD on gait of the individual, which are ready-to-analyze. The algorithm operates as follows:

First, two data frames are created (left and right footwear data frames), each one containing their respective 11 sensor signals and timestamps. Then, the sensor signals from each footwear data frame are added together on each instant *k* acquired:

$$\sum_{i=1}^{i=n} S_{i,k}^{Left} \qquad \sum_{i=1}^{i=n} S_{i,k}^{Right}, \tag{6.1}$$

where *n* is the number of sensors of the sensing shoe, and *S* the value of force of the sensor number *i* on the instant *k*. The addition of every sensor for each sensor-footwear reduces the dimensionality of the initial data frames, which simplifies the process to find the indexes of the start and end of each step.

The data frames contain now only 2 vectors, the total ground reaction force of the footwear on every instant *k* acquired and their respective timestamps. In Figure. 6.2, the total ground reaction force of the right footwear data frame is shown (black signal + red signal).

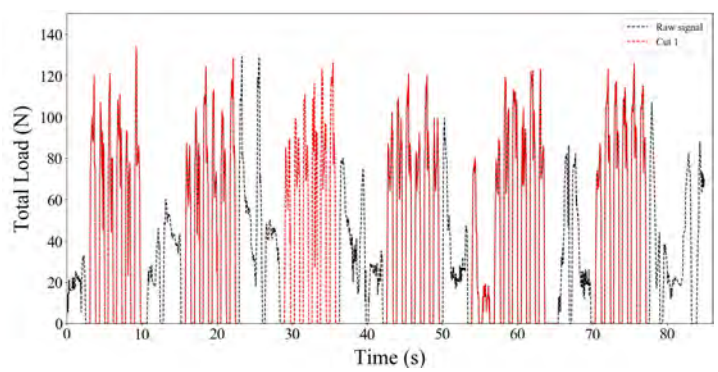


Figure 6.2. Inter-static position gait data segmented.

Next, by a zero-crossing algorithm, a list with the indexes of the start and end of every step *j* is obtained for both left and right footwear data frames, and the duration for each step *j* (d_j) is calculated:

$$d_j = step\_time\_end_j - step\_time\_start_j. \tag{6.2}$$

As the individuals walking speed was between 1.18 m/s and 1.42 m/s, the step's duration was smaller than 1.5 s. Also, as the individuals paused at least 2 seconds every half lap, 2 seconds static positions (detected as steps) surround the relevant gait cycles of the test. Subsequently, the static positions are flagged by comparing the duration of the steps against a threshold $d_j = 1.5\ s$. This threshold works fine, as the mean duration of the real recorded steps is less than a second. Then, using the flags, the first segmentation of the data is performed, resulting on 2*v* segments (Figure 6.2, red signals) for each data frame. Afterwards, for each pair of segments, first right segment and first left segment and so on, the first step and last step (Figure 6.3, red signals) of the segment were detected and removed. These first and last steps removal was proposed due to an observed variation on load intensity and distribution generated by the acceleration and deceleration at the start and the end of the walk. The removal of these steps allows obtaining the characteristic PPD on the gait of an individual and thus accomplish an objective comparison between gait segments. After removing the first and last step of each segment, the result are the blue signal segments shown in Figure 6.3.

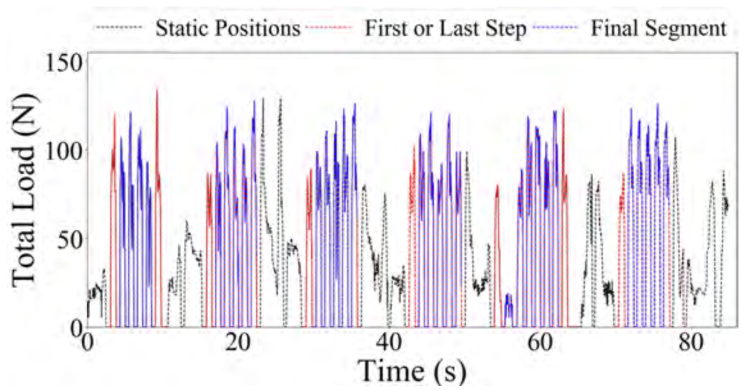


Figure 6.3. Proposed gait-slicing process.

The output of the gait-segmentation algorithm are the blue signal segments; for this example, twelve gait-segments, six for each sensor shoe, are obtained. These segments are the input for the signal standardization algorithm, which is described in the subsection below.

6.2.2.2 Signal standardization algorithm

The signal standardization algorithm takes each gait-segment generated by the segmentation algorithm and generates a *k*-length standardized data frame for each step in the gait-segment. The algorithm operates as follows:

1. First, the algorithm uses the Equation 6.1 to calculate the total GRF for each gait-segment. As the gait-segments contain variable steps, a zero-crossing algorithm is used to get the index of both the start and the end of each step.

2. Then, for each step, the index of the points A, B, C, D and E are identified according to Figure 6.4.

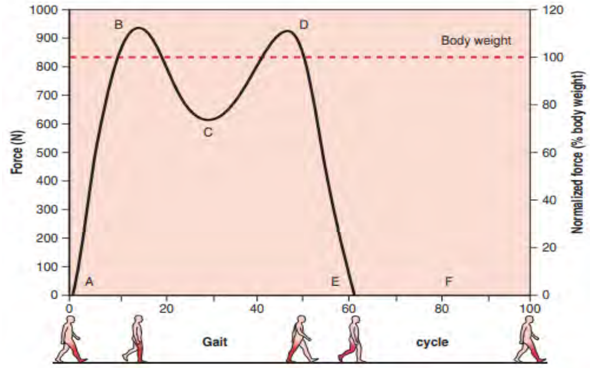


Figure 6.4. Division of gait cycle

3. Once, the indexes are obtained, lineal splines are defined between A-B, B-C, C-D, and D-E, for each one of the eleven sensor signals. With these splines, a standardized cloud of points is generated for each of the sections of the step (A-B, B-C, C-D, and D-E), for instance 50 points, this allows creating length standardized data frames of 11 x 200 (11 sensors, 200 time instances), which can be used for gait-analysis applications.
4. Finally, each length standardized step data frame is converted into a grayscale heatmap, so the maximum force is represented by a 255, and 0 N is represented by a 0. These heatmaps contain the data of the eleven sensors (vertical axis) during the time duration of the step (horizontal axis).

An example of a data frame containing the eleven sensor signals of a step is shown in Figure 6.5a, and the corresponding heatmap to that data frame is shown in Figure 6.5b.

a) b)

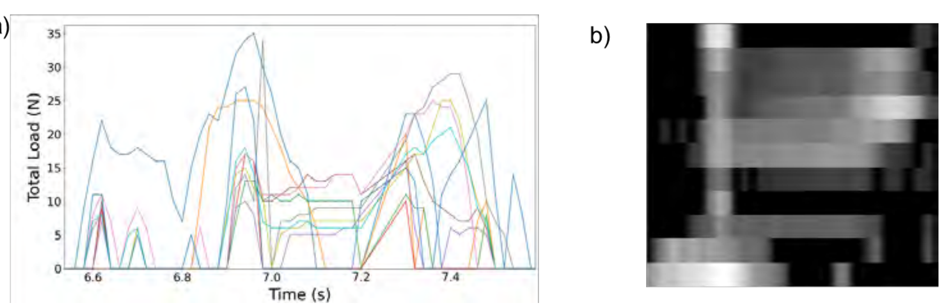


Figure 6. 5 a) GRF signals of a step of left sensor shoe b) Grayscale heatmap of step

The data frame containing the force data can be used for example to train deep neural networks such as the Long-Short Term Memory (LSTM), or can be analyzed with any time-series analysis technique, the grayscale heatmap can be used in classification tasks for example with convolutional neural networks (CNN).

Now that the hardware, software, and preprocessing algorithms have been described, a gait analysis proof of concept experiment is presented.

6.3 GAIT GRF PATTERN CLASSIFICATION: A PROOF OF CONCEPT

Gait pattern classification is one among many techniques that can be useful to create auxiliary tools for clinical diagnosis. In this section, a proof of concept of classification of GRF patterns on gait is presented. Three gait patterns were recorded and used to train a convolutional neural network. The data was acquired with the proposed sensor footwear (Chapter 4) and methodology (Section 6.2.1). A description of the methodologies to generate the data for this experiment is presented in the following subsection.

6.3.1 Acquisition of gait patterns

For this experiment, three gait patterns were proposed. A normal or “control” GRF pattern, and two pathological gait patterns. To generate pathological GRF patterns on gait, a piece of plastic of 3 cm x 4 cm x 1 mm was placed on the left sensor footwear (for this experiment, only the left sensor shoe was used). In Figure 6.6, the placement of the plastic piece is depicted for each gait pattern.

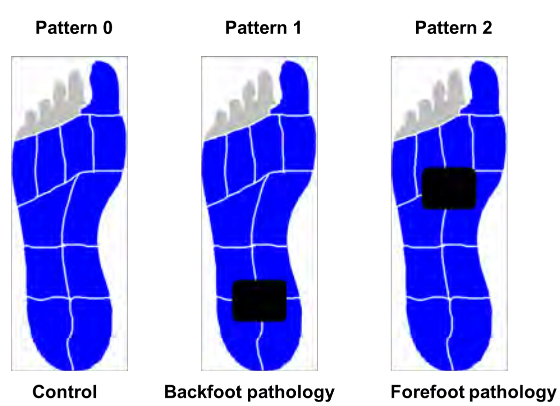


Figure 6.6. Setup of foot perturbations for three different GRF patterns on gait

Pattern 0 consists of a “normal” GRF on gait, pattern 1 consists of a gait pattern with an anomaly in the heel zone of the foot, and pattern 2 consists of a gait pattern with an anomaly on the metatarsal zone of the foot.

For this experiment, fifteen gait sessions were recorded for each sensor footwear setup. Using the preprocessing gait data pipeline, 350 steps were extracted for each pattern, for a total of 1050 images.

In Figure 6.7, images of the three GRF patterns on gait are shown.

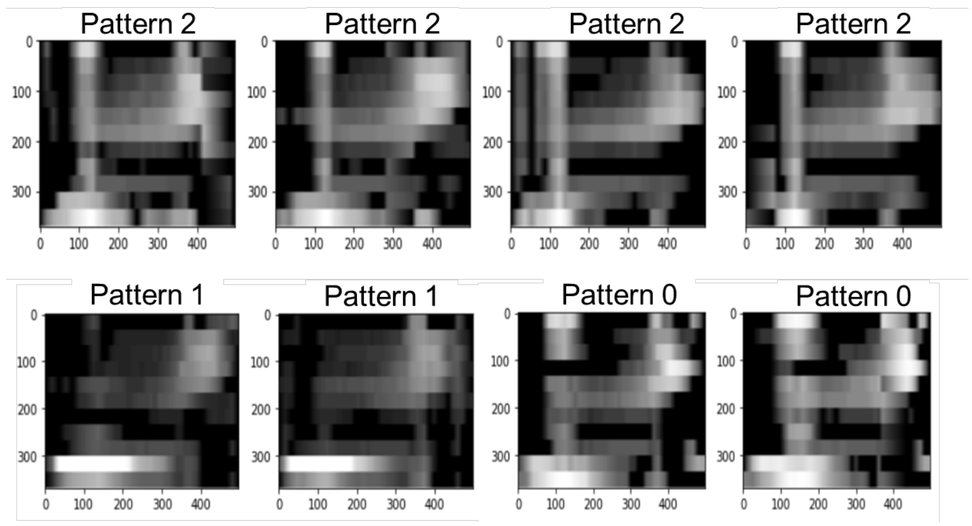


Figure 6.7. Preprocessed step images for gait pattern classification

Following standard practices to build a machine learning model, the dataset was divided in three sets:

- Training set: 70% (~750 images)
- Validation set: 15% (~150 images)
- Test set: 15% (~150 images)

The training set is used to adjust the classifier model, the validation set is used to assess if the model is over or under fitted and to adjust the hyperparameters of the model. Finally, the test set is used once the final model is trained and validated. The test set helps to evaluate the performance of the model and its ability to correctly classify new instances (generalization). A convolutional neural network was proposed to classify the gait pattern images. In the following subsection, the description of the model is presented.

6.3.2 Classifier Architecture

The TensorFlow framework was used to implement the neural network. The proposed architecture for the classification problem is integrated by two convolutional layers, followed by a pooling layer, then the output is flattened and connected to a fully connected layer, and finally, the output layer is another fully connected layer with the number of classes of the classification problem, for this case, three. The output layer has a softmax activation function, which outputs the probability of the GRF pattern image to belong to each class. In Figure 6.8, the diagram of the CNN's architecture is shown.

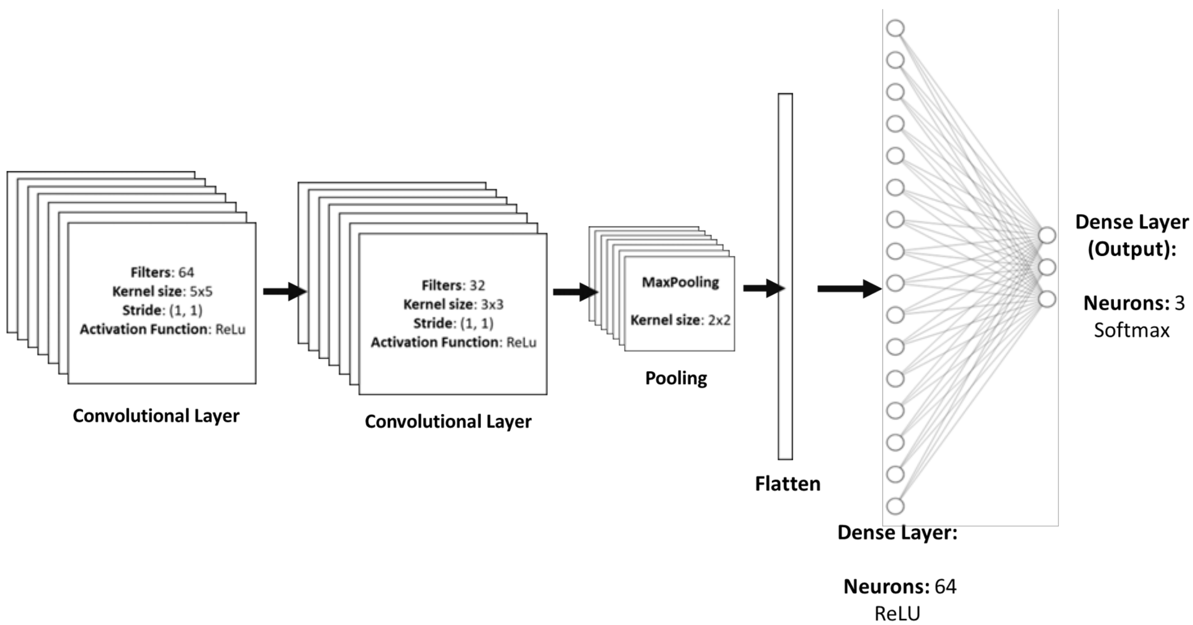


Figure 6.8. Convolutional Neural Network Architecture.

Loss function

A sparse categorical cross entropy cost function was selected for the model. This function is used to measure the performance of classification models (binary or multiclass) which outputs are expressed as probabilities to belong to a class (output between 0 and 1). The cross-entropy loss increases when the probability diverges of the target of the instanced input. For example, predicting a probability of 0.012 when the correct observation is 1, would result in a high loss. A perfect model, would predict a probability of 1, and thus, zero loss.

Optimizer

The Adam optimizer was used on this model. It is one of the most popular optimizers, and a good choice as a starting point when training a model. The Adam optimizer is computationally efficient and can operate with noisy data, also, normally its hyperparameters need generally few adjustments.

6.3.3 Results

The model was trained 20 epochs with the Adam optimizer, the number of epochs is extremely low. However, the model adjusted rapidly to the data, and obtained low cost in both the training and validation set, thus, rejecting the probability of overfitting.

The loss and accuracy graphs are shown in Figure 6.9

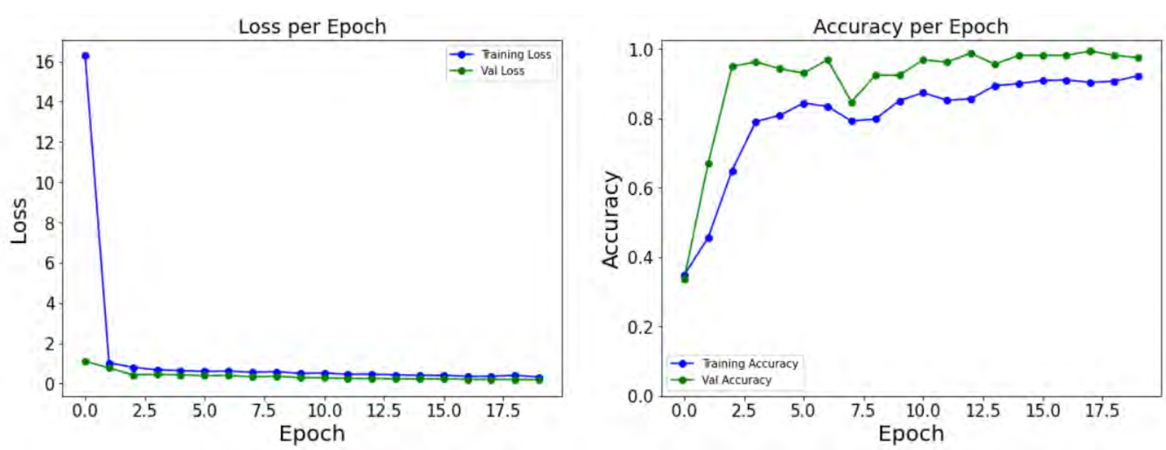


Figure 6.9. a) Training and validation loss b) Classification accuracy with training and validation data sets

A possible answer to the extremely low iterations needed to fit the model, even though the architecture was simple, is that the classification problem we proposed was easy, the data was lineally separable and thus, the model learned quickly to distinguish between the GRF patterns on gait.

Finally, once the model was trained and validated, the generalization of the model was evaluated with the test set (157 instances that the models never "saw"). The classification accuracy of the model was of 98%. To depict the accuracy results, a confusion matrix is shown in Figure 6.10.

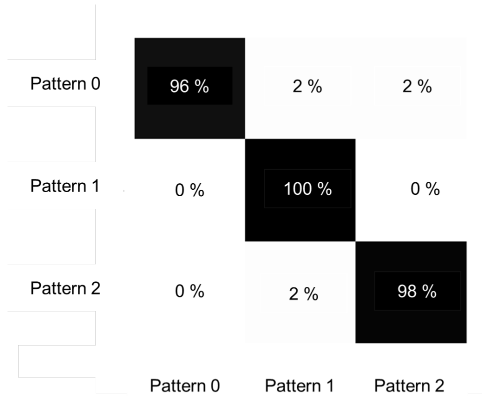


Figure 6.10. Confusion matrix

It can be observed that only three of the 157 instances were mistakenly classified. A F1_score of 0.98 was achieved, which indicates that the trained model has high accuracy and low false positive and false negative rates. However, the high accuracy results with such a simple architecture suggest that the proposed classification problem was too easy to solve. On future work, the acquisition and classification of gait data of real pathologies is planned.

6.4 CONCLUSION OF THE CHAPTER

In this chapter, the proposal and development of a test acquisition methodology and a preprocessing gait data pipeline were presented; Both, the methodology and the algorithm, were created to automate and standardize the data acquisition and preprocessing tasks, to create objective ready-to-analyze data for any GRF analysis application.

Finally, a proof of concept of classification of GRF patterns on gait was demonstrated. Three different gait patterns were acquired with the developed sensor footwear and the newly introduced acquisition methodology, and then, the data was preprocessed with the developed preprocessing gait data pipeline. Subsequently, a CNN was trained to classify the data. High accuracy results were obtained, which demonstrates the potential of gait pattern classification to develop auxiliary tools for clinical diagnosis of gait anomalies.

CHAPTER 7:

RESULTS AND DISCUSSION

7.1 RESULTS OF THE PROJECT

In this thesis work, the design, development, characterization and deployment of a gait monitoring and analysis system has been presented. In this section the main results of the project are reviewed, beginning with the development of the sensor footwear.

Sensor Footwear

There were two main achievements obtained through the development of the prototype:

The first one, is the demonstration of the importance of the in-shoe characterization of the sensors to improve the accuracy of the ground reaction forces' (GRF) measurements. When designing the sensor footwear, one of the most important aspects that we focused on, was to obtain accurate GRF measurements. To achieve this, reliable sensor characterizations were needed. In the literature of GRF monitoring using wearables such as sensor insoles or footwear, vague or non-existing characterization information is presented. Leading to assume that authors obtained a generic force-voltage sensor response, and then used it to estimate the forces of every sensor. This would work if all the sensors behaved indeed equally, and there were no other sources of variability. So, we asked ourselves the following question:

How much does the footwear affect to the sensor's response?

To answer this question, we tested the acquired sensors. The sensors were tested by applying the same load, on the footwear, only on the insole, and outside the footwear and insole. First, we tested the sensors outside the footwear and insole, and a coefficient of variance (CV) of 2.62% between the sensors' response was obtained. This demonstrates, that if used on the same surface, a generic sensor response would suffice to estimate the applied force on the sensor. But then, we tested the same loads on the sensors on the insole, and a CV of 9.35% was obtained, which means that the insole, though it is flat, adds variability to the measurements. Furthermore, the insole (with the sensors on it) was installed on the footwear (a flattened-sole footwear), and the same loads were applied to the sensors, this resulted on a 16.61% CV, which means that the position of the sensor on the footwear affects the sensor's response, even on flattened-sole footwear. These variations lead us to the inevitable acknowledgement of the importance of in-shoe characterization, which proves that at least for quantitative measurements of GRF, sensor insoles should not be used on different shoes, as not only GRF accuracy is decreased, but also the natural plantar pressure distribution (PPD) of the individual is modified due to the footwear sole, disabling objective PPD comparisons between individuals. To address this variability, we decided to make an extensive in-shoe sensor characterization. In-shoe characterization allows compensating the inherent variability of the insole and footwear, and thus, resulting in accurate GRF measurements.

It is worth to be mentioned, that not all gait monitoring applications are dependent on accurate GRF measurements, for example, the ones that rely on activity detection. However, if GRF wearable systems aim to achieve accurate GRF measurements, in-shoe characterization must be considered, as it compensates the variability of the footwear.

The second achievement, is the resolution improvement on the GRF measurements obtained through the self-calibration algorithm. As stated in Chapter 4, a fixed force measurement range (FMR), for instance, 0 N – 200 N, may be enough to monitor most individuals in low impact activities such as walking, but this FMR is not optimal for every user. During the assessment period of the system in the consulting room, we observed, that light -weighted individuals applied a maximum of 50 N or even 25 N per sensor, which represents only the 25% or 12.5% of the total FMR respectively, which results in limited resolution when monitoring light-weighted individuals. With such a limited resolution, it may be difficult to quantify reliably small variations on the gait pattern of a patient.

To solve this, we proposed a dynamical self-calibrating circuit with four FMR: 0 N – 25 N, 0 N – 50 N, 0 N – 100 N, and 0 N – 200 N; these FMR allow monitoring the PPD of lightweighted individuals like children and of overweighted adults below 100 Kg on low impact activities like walking and going up or down stairs.

The self-calibration circuit dynamically adjusts the FMR of the sensors, depending on the maximum force applied by the user. The self-calibration enables the utilization of the whole FMR, which optimizes the measurements' resolution for each individual, independently of their weight. The resolution enhancement of the self-calibration algorithm can be demonstrated with the comparison of the characterization curves shown in figure 7.1. On the graph, the characterization curves of a sensor on the metatarsal zone for 0 N - 25 N and 0 N - 200 N FMR are shown. As the developed sensor footwear operate with a 12-bit ADC in a range of V_{in} 0.625 - 3.3 V, 3320 ADC units are used for the GRF acquisition. The next thought experiment is proposed: How does the resolution compares when 0 N - 25 N and 0 N - 200 N FMR are used and the user can apply only a maximum force of 25 N on any sensor?

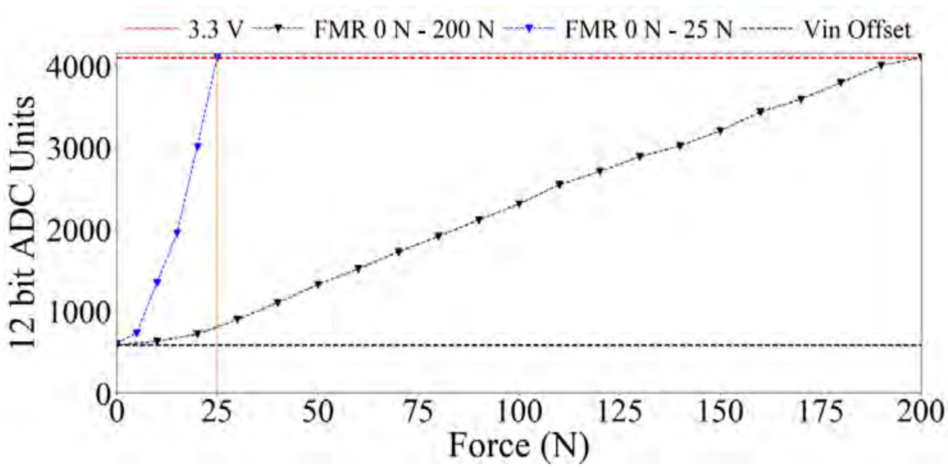


Figure 7.1. Characterization curves for 0 - 25 N and 0 - 200 N FMR.

In Figure 7.1, it can be observed that if the 0 N - 200 N FMR was used to record the light-weighted individual (25 N maximum force), the measurements would lie on approximately 200 out of 3320 available ADC units, instead if the system was self-calibrated to the 0 N - 25 N FMR, the measurements of the sensors would use the 3320 available ADC units, resulting on a 16.66 times resolution enhancement.

With both the in-shoe characterization, and the self-calibration algorithm and circuit, the developed sensor footwear is enabled to obtain accurate GRF measurements during daily activities such as walking, going up or down stairs, among other low impact activities, with an optimized FMR for any user, independently of their weight.

Moving on, the review of the results regarding the gait monitoring system as a whole are described below.

Gait monitoring system

The gait monitoring system is integrated by the developed sensor footwear described in Chapter 4, the software tools presented in Chapter 5, and the methodologies and processing algorithms shown in Chapter 6. After the sensor footwear and monitoring software were tested, and also thanks to a collaborator of the project, the gait monitoring system was deployed on a rheumatologist's consulting room. The PC monitoring software was installed on the specialist's computer, and a router was set up on the consulting room to create a wireless local area network for the sensor footwear to connect.

During three months, the gait monitoring system was evaluated by the specialist. The patients were asked if they wanted to test the sensor footwear, and walk a couple of laps on a corridor to monitor their gait. During the evaluation period, 70 individuals of a diverse group of age, weight, and with or without knee symptoms, tried the proposed sensor footwear. The tests were recorded with the proposed methodology and preprocessed with the gait-segmentation algorithm, in which, the gait cycles between turns, and static positions are segmented. On these gait segments, the first and last left or right step are also sliced, as these steps have a different amplitude and force distribution than the middle steps, due to the acceleration or deceleration of the gait. The segmented middle gait cycles represent the characteristic GRF on gait of an individual. Then, some statistics about the characteristic GRF on gait were calculated for each individual. For example, the step cadence, average and standard deviation of step forces and durations.

Also, the distribution of the GRF on the left and right foot, on the medial and lateral section of the foot, and on the backfoot, midfoot and forefoot were estimated. The distributions of the GRF mentioned, were used to create a representation of the tendency of GRF on gait segments, this representation is shown in Figure 7.2.

In Figure 7.2, the estimated tendency is represented by quantifying the sensor footwear data in a tridimensional space. The first dimension represents the percentage load on the left or right foot of the subject, the first coordinate is situated from 0 to1, if the load of the user predominates towards the right foot; and from -1 to 0 if the load on left foot predominates. The second dimension is represented by the percentage inner or outer load, the sensor's data is divided depending on their position on inner or outer part of the foot. The coordinate is situated from 0 to 1 if the load of the user predominates on the outer part of the foot; and from -1 to 0 if the load predominates on the inner part of the foot. Then, the third dimension represents the percentage load on rearfoot or forefoot, the coordinate is situated from 0 to 1 if the load predominates towards the forefoot; and from -1 to 0 if the load predominates towards the rearfoot.

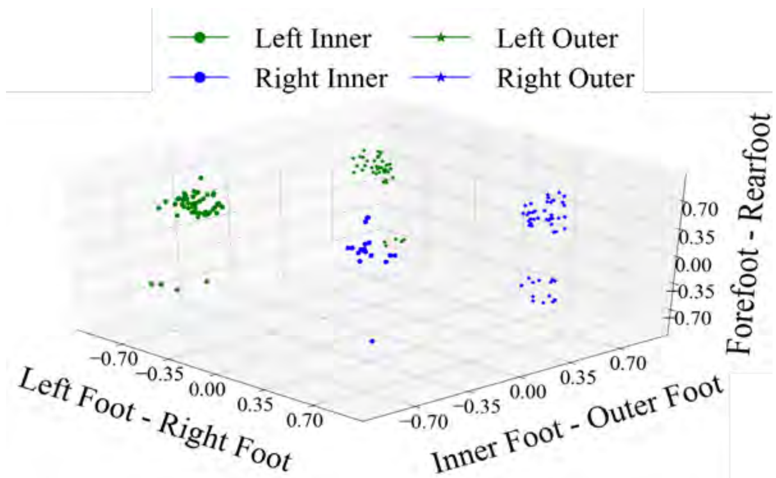


Figure 7.2. GRF tendency on gait tests' segments

This is only a representation of the quantification of the sensor data, which was used to assess the system´s performance during the evaluation period at the consulting room. This representation shows graphically where the gait GRF tendency of every monitored user is situated. For future work, further analysis with data collected by the developed GRF monitoring system will be presented, as the goal of the system and algorithms is to create a gait database of a wide variety of pathologies, in which, due to the design and development considerations of the sensor footwear, the signals obtained can objectively be compared between patients to create auxiliary tools for clinical diagnosis and rehabilitation analysis.

7.2 DISCUSSION

Worldwide, the design and development of sensor footwear has created interest due to its potential role to provide auxiliary tools for diagnostic and rehabilitation of a wide range of pathologies. In this work, the design and development of a gait monitoring and analysis system was presented, and in this section, the results obtained through this thesis are discussed, starting from the design of the sensor footwear.

Probably, the first decision made when developing a sensor footwear to monitor ground reaction forces (GRF), is the selection of the sensor's technology. On wearable sensor insoles or footwear, technologies such as capacitive, resistive, piezoelectric, optical, among others have been implemented. Each one of them provides different advantages and disadvantages. For the developed prototype, we have used force sensing resistors (FSRs), which are one of the popular cost-precision choices, however, the non-linearity of the response of the sensor may affect the accuracy of the measurements. To reduce this non-linearity, signal conditioning circuits such as the non-inverting amplifier can be implemented.

This leads to another decision, the definition of the force measurement range (FMR). The FMR is not only determined by the sensor´s mechanical properties and limitations, but also by the signal conditioning circuit. The FMR is defined depending on the weight of the user and the activity to monitor. So, the FMR would be wider for high impact activities than for walking at natural speed, or would be wider for heavy weighted users, than for children or low weight women. Naturally, devices with wider FMR could be used to monitor low impact activities and light-weighted individuals, however, the full extension of the FMR would not be used, resulting on limited resolution on the GRF measurements. To address this problem, we have proposed, designed and implemented a self-calibrating signal conditioning circuit, which enables a dynamical FMR for the sensor footwear. Through a calibration phase, the sensor footwear detects the maximum force applied by the user, and selects the optimal FMR for each user, improving the resolution of GRF measurements up to 16.66 times.

Then, one of the most important aspects regarding the accuracy of the GRF measurements is the characterization of the sensors. As the literature of the design and development of sensor footwear was revised, characterization specifications were rarely found, and when they were presented, the authors did not deepen on it. This leads to assume that a generic sensor response curve is used to obtain GRF measurements from all sensors. This may not have an effect, when measuring the sensors outside the footwear, but it does have an effect when measuring inside the shoe. During our experimentation, significative variations on the response of the sensors were identified between sensors on the same position on left and right shoe, and also on sensors along the same shoe, even if a flattened-sole footwear was used. A coefficient of variation (CV) of 2.62 %, was obtained for the sensors outside the shoe, and CV of 12.01% and 8.37% were calculated for the left and right footwear, respectively, for the in-shoe characterization. These variations lead us to the inevitable acknowledgement of the importance of in-shoe characterization, which proves that at least for quantitative measurements of GRF, sensor insoles should not be used on different shoes, as not only GRF accuracy is decreased, but also the natural plantar pressure distribution (PPD) of the individual is modified due to the footwear sole, disabling objective PPD comparisons between individuals. In-shoe characterization improves the accuracy of the PPD monitoring systems on GRF acquisition, also the implementation of flattened-sole footwear to monitor PPD standardizes PPD tests, allowing objective inter-patient gait comparison.

Finally, an aspect of sensor footwear design that may seem superficial, but it is still relevant, is the utilization of bulky electronics, which result in the need of strapped-on electronics to the leg or hip of the user. Strapped-on electronics affect the natural gait of the user. This circumstance adds a random variable to the measurements of the studies, because each user may compensate the discomfort of the strapped-on electronics and hanging wires in their own way. This is not only an aspect to take care for in research and clinical applications, but a critical concern when aiming to deploy wearable systems in real life applications, as the comfort and social acceptance of the devices are important aspects that must be considered when designing wearable technologies.

As for today, wearable gait monitoring systems are used mainly in research laboratories. To further promote the use of gait monitoring systems in consulting and rehabilitation rooms, we have developed PC monitoring and analysis tools to provide GRF statistics that may be useful to assess the evolution of gait of patients during stages of their gait-related pathologies and their rehabilitation and follow up. For now, the proposed system provides a real time visualization, test recording, cloud database synchronization, the reproduction of recorded tests, and the display of GRF statistics. Other systems provide the analysis of center of pressure, extraction of several gait parameters, among other features. On future work, more features will be developed and integrated to the PC software.

On the other hand, ambulatory applications such as activity detection, fall risk assessment, energy consumption estimation, among others have been demonstrated in the literature. In this work, we have developed a smartphone tool to record gait. However, also on future work, we intend to develop a feature to assess the evolution of gait during real life activities, this feature may serve as an auxiliary tool to detect gait abnormalities, or to track the improvement of the patient’s gait during rehabilitation.

Moreover, we have proposed a test acquisition methodology and a gait preprocessing data pipeline to standardize the sensor data acquired with the developed system. The test acquisition methodology consists on a movement protocol to record gait on a corridor. These recorded tests are then preprocessed with our algorithm, which was designed to complement the test acquisition methodology. The preprocessing algorithm automatically segments the relevant gait cycles of the test, to obtain the individual’s characteristic GRF on gait. Then, these gait cycles are standardized in amplitude and vector size, thus, they can be objectively compared with the tests of other individuals.
To evaluate our sensing system, methodologies and algorithms, we have demonstrated a GRF pattern classification proof of concept. In this proof of concept, we have artificially created GRF patterns by applying repeatable perturbations to the foot, and then acquired an equal number of gait tests for each pattern with our proposed methodology, and preprocessed the recorded data with the developed data pipeline. Finally, we fed a

convolutional neural network to learn and classify the GRF patterns. We found success on this experiment, by classifying correctly more than 95% of the gait cycles.

Undoubtedly, the potential of gait monitoring and analysis is huge. However, its implementation on real life circumstances will highly depend on the development of robust, reliable, and low-cost monitoring systems and by demonstrating that the developed analysis tools would bring a real utility as auxiliary tools for diagnosis, rehabilitation, or other ambulatory applications.

CHAPTER 8:

CONCLUSION AND RECOMMENDATIONS

8.1 CONCLUSION

- ✓ The design and development of a sensor footwear prototype was presented. Several considerations made on the sensor footwear design and development were described to avoid mechanical noise on the sensors.

- ✓ The importance of in-shoe sensor characterization was demonstrated, as significative variations on the sensor's responses (coefficient of variation (CV) = 16.61%) were found along the backfoot, midfoot, and forefoot zones of the foot (on a flattened sole shoe), in contrast to the CV of 2.62% on the sensor response outside the footwear. The increase of variation on the sensor response inside the footwear demonstrates that generic sensor response curves introduce errors in the force measurements, which can be compensated with in-shoe sensor characterization.

- ✓ A dynamical self-calibrating circuit was proposed. The sensor footwear detects the maximum applied force through a calibration phase, then, by a logic-decision program the feedback resistor (Rf) of a non-inverted amplifier signal conditioning circuit is switched to adjust the force measurement range (FMR) optimally to the weight of the user, and thus maximizing the resolution of ground reaction force (GRF) measurements for every individual.

- ✓ Four characterization curves were obtained for each sensor (one for each proposed FMR) using a universal testing machine. Then, shoe-specific characterization sheets were made and integrated to the gait monitoring software, to obtain accurate GRF measurements from sensor responses.

- ✓ The design of the program of the microcontroller was presented, where the two sections of the program were described: (1) the initialization routine of the microcontroller, in which the sensor footwear initializes the adc, and SD memory modules, and connects to the selected network mode. And (2) the main loop of the program, where the microcontroller handles and executes the commands of the user interfaces.

- ✓ Two software solutions were presented to interface the user with the sensor footwear. The first one, a PC monitoring software that was designed for real time visualization of the GRF during gait on motion laboratories, consulting and rehabilitation rooms. And the second one, a smartphone application designed to monitor gait during real life activities.

- ✓ Two network setups were proposed to communicate the developed user interfaces to the sensor footwear. A WLAN network setup was proposed for indoor gait monitoring applications in gait labs, or consulting and rehabilitation rooms. Also, a point to point network was proposed for outside-the-lab gait applications.

- ✓ A test acquisition methodology and a preprocessing gait data pipeline were proposed. Their main function is the standardization of the data acquisition and preprocessing tasks to create objectively ready-to-analyze data for any GRF analysis application.

- ✓ The deployment of the developed gait monitoring system on a consulting room was presented. During an evaluation period, the system was tested with real patients and its performance evaluated by a specialist. The collected data was used to assess the system´s performance. Also, a representation of the GRF tendency of the patient's gait, and insights on the patient data were presented.

- ✓ Finally, a proof of concept of classification of GRF patterns on gait was demonstrated. Three different gait patterns were acquired with the developed sensor footwear and the newly proposed acquisition methodology, then, the data was preprocessed with the developed preprocessing gait data pipeline. Subsequently, a convolutional neural network (CNN) was trained to classify the data. High accuracy results were obtained, which demonstrates the potential of gait pattern classification to develop auxiliary tools for clinical diagnosis of gait anomalies.

8.2 RECOMENDATIONS

In this work, the design, development, characterization and deployment of a gait monitoring and analysis system has been presented. However, there are still improvements to make and new features to develop and implement to the system. Some ideas are enlisted below.

Sensor Footwear

- In the actual prototype, the sensor insole is connected with wires. Considerations were made in the design and development of the insole to avoid mechanical error due to the wire. However, this process is slowly and carefully handcrafted. The implementation of flexible printed circuits is proposed to remove the wires, thereby, facilitating the construction of the proposed sensor insoles.

- It is also proposed the design and construction of a smaller printed circuit board (PCB) and the utilization of a smaller battery to assure maximum comfortability and social acceptance in the final version of the sensor footwear.

- The integration of inertial measurement unit sensors to the sensor footwear is proposed to obtain acceleration, angles and moments of the lower limb joints to complement gait analysis.

Software Features

- The development of an automatized report generator feature is proposed. This report would include statistics about gait parameters and their variability in a single test, and if the patient had previous sessions, a comparison of how the gait parameters have shifted.

- The development of an activity detection feature on the smartphone app is proposed. This feature could be implemented to monitor energy expenditure, or to evaluate the risk of fall in elder people.

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