Faculty of Engineering of the University of Porto

A Novel Machine Learning Algorithm for Classification of Gait Phases From EMG Data

Miguel Carmo

Preparation of the Dissertation
Master in Biomedical Engineering

Supervisor: João Manuel R. S. Tavares (phD)

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Abstract

Gait analysis is the study of human gait. One of the fundamentals of gait analysis is the human gait cycle, which splits human gait into a series of gait periods and gait events, which act as the boundary between the various periods. By accurately detecting gait events and periods in real-time, researchers can develop control strategies for functional electric stimulation (FES) and motorised prosthetics (MPC). One method of detecting gait events and periods is to use electromyography (EMG) sensors, since they are unaffected by many of the problems which sensors like inertial measurement units and footswitches have. However, EMG sensors require the use of complex machine learning (ML) classification algorithms to detect gait events and have relatively low accuracies when compared to other sensors. For this reason, many researchers have tried to develop robust algorithms that can accurately detect gait events using EMG sensors, with varying success.

The goal of this dissertation is to develop a ML algorithm that can improve on classification accuracies and robustness of previous studies. To achieve this, EMG data will be acquired synchronously with a reference system, such as force platforms, and labelled in order to train the ML algorithm. Time domain features will be used to train the algorithm and classify unlearned data, and the algorithm’s performance will be evaluated with the average and standard deviation of event detection delay between the classification algorithm and the reference system.

Studies have shown that detection delays of more than 125ms negatively affect motorised prosthetic users and FES patients, so it is extremely important that classification delays are consistently below this value. To validate the algorithm’s robustness for real-life applications, the classification delay should not be affected by factors such as slopes, stairs and external loads on the user. Another crucial goal is that no false positive gait events should be detected by the system, since these can lead to a loss of balance or even the user’s fall.

This report served the purpose of analysing the different techniques and steps used by researchers to develop gait event classification algorithms, from EMG signal acquisition and processing, to the fundamentals of human gait and the gait cycle, and finally the different approaches and steps of developing a machine learning algorithm.
Resumo

Análise de marcha é o estudo da marcha humana. Um dos conceitos fundamentais da análise da marcha é o ciclo de marcha humana que divide a marcha humana numa série de períodos, separados por eventos específicos. Pela deteção precisa de eventos e períodos de marcha em tempo real, investigadores conseguem desenvolver estratégias de controlo para estimulação elétrica funcional (FES) e próteses motorizadas (MPC).

Um método de deteção de períodos e eventos de marcha consiste em utilizar sensores de eletromiografia (EMG), já que estes não são afetados por muitos dos problemas usualmente encontrados em sensores como sensores de inércia e footswitches. Contudo, sensores EMG requerem o uso de algoritmos de classificação complexos de Machine Learning (ML) para detetar eventos de marcha e, quando comparados com o uso de outros sensores, obtém exatidões e precisões relativamente menores. Por esta razão, muitos investigadores têm vindo a tentar desenvolver algoritmos que conseguem, com grau variado de sucesso, detetar com exatidão eventos de marcha usando sensores EMG.

O objetivo desta dissertação consiste em desenvolver um algoritmo de ML capaz de melhorar a precisão e robustez dos mecanismos de classificação usados em estudos anteriores. Para atingir este fim, dados de EMG serão adquiridos simultaneamente com um sistema de referência, como plataformas de força e rotulado de modo a ser possível treinar o algoritmo de ML. Características de time domain do sinal serão usadas para treinar o algoritmo e classificar os unlearned data. A performance do algoritmo será avaliada através do cálculo da média aritmética e do desvio padrão correspondentes ao atraso na deteção do evento entre o algoritmo de classificação e o sistema de referência.

Estudos mostraram que atrasos na deteção de eventos de mais de 125ms afetam negativamente os utilizadores de MPC e de FES. Por isso, é extremamente importante que os atrasos na classificação se mantenham abaixo deste valor. Para validar a robustez do algoritmo para aplicações de vida real, o atraso na classificação não deverá ser afetado por inclinações, escadas e cargas externas aplicadas ao utilizador. Outro objetivo crucial dita que é imperativo que não haja registo de falsos eventos de marcha pelo sistema, visto que estes podem levar à perda de equilíbrio ou até a quedas.

Este relatório serviu, assim, o propósito de analisar diferentes técnicas e passos usados por investigadores no desenvolvimento de algoritmos de classificação de eventos de marcha humanos, desde a aquisição do sinal EMG e ao seu processamento até aos conceitos fundamentais da marcha humana do ciclo de marcha, incluindo ainda as diferentes abordagens e passos necessários para o desenvolvimento de um algoritmo de ML.
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<table>
<thead>
<tr>
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<th>Definition</th>
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<tr>
<td>ANFIS</td>
<td>Adaptive neuro-fuzzy inference system</td>
</tr>
<tr>
<td>AR</td>
<td>Autoregressive coefficients</td>
</tr>
<tr>
<td>BIC</td>
<td>Bayesian information criteria</td>
</tr>
<tr>
<td>d-EMG</td>
<td>EMG Derivative</td>
</tr>
<tr>
<td>e-EMG</td>
<td>EMG Envelope</td>
</tr>
<tr>
<td>EMG</td>
<td>Electromyography</td>
</tr>
<tr>
<td>FA</td>
<td>Feet Adjacent</td>
</tr>
<tr>
<td>FD</td>
<td>Frequency domain</td>
</tr>
<tr>
<td>FES</td>
<td>Functional Electrical Stimulation</td>
</tr>
<tr>
<td>FF</td>
<td>Foot Flat</td>
</tr>
<tr>
<td>FSR</td>
<td>Force Sensing Resistors</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic Algorithms</td>
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<tr>
<td>GP</td>
<td>Gait Partitioning</td>
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<tr>
<td>HIST</td>
<td>EMG Histogram</td>
</tr>
<tr>
<td>HO</td>
<td>Heel Off</td>
</tr>
<tr>
<td>HS</td>
<td>Heel strike</td>
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<tr>
<td>IC</td>
<td>Initial Contact</td>
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<tr>
<td>i-EMG</td>
<td>Integrated EMG</td>
</tr>
<tr>
<td>Im-EMG</td>
<td>Intramuscular EMG</td>
</tr>
<tr>
<td>IMUs</td>
<td>Inertial measuring units</td>
</tr>
<tr>
<td>KEMG</td>
<td>Kinesiological Electromyography</td>
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<tr>
<td>LDA</td>
<td>Linear discriminant analysis</td>
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<tr>
<td>MAV</td>
<td>Mean Absolute Value</td>
</tr>
<tr>
<td>mGAS</td>
<td>Gastrocnemius medialis</td>
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<tr>
<td>MNP</td>
<td>Mean Power</td>
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<tr>
<td>MPC</td>
<td>Motorised prosdissertation control</td>
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<tr>
<td>MUAP</td>
<td>Motor unit action potential</td>
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<tr>
<td>NWS</td>
<td>Non-Wearable Sensors</td>
</tr>
<tr>
<td>OIC</td>
<td>Opposite initial contact</td>
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<tr>
<td>PCA</td>
<td>Principal component analysis</td>
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<tr>
<td>PKF</td>
<td>Peak Frequency</td>
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</table>

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>PS</td>
<td>Pre-Swing</td>
</tr>
<tr>
<td>RF</td>
<td>Reaction force</td>
</tr>
<tr>
<td>RMS</td>
<td>Root Mean Square</td>
</tr>
<tr>
<td>r-RMG</td>
<td>Raw EMG</td>
</tr>
<tr>
<td>SD</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>sEMG</td>
<td>Surface EMG</td>
</tr>
<tr>
<td>SSC</td>
<td>Slope Sign Changes</td>
</tr>
<tr>
<td>TA</td>
<td>Tibialis anterior</td>
</tr>
<tr>
<td>TD</td>
<td>Time domain</td>
</tr>
<tr>
<td>TO</td>
<td>Toe off</td>
</tr>
<tr>
<td>TS</td>
<td>Terminal Stance</td>
</tr>
<tr>
<td>TV</td>
<td>Tibia Vertical</td>
</tr>
<tr>
<td>WL</td>
<td>Waveform Length</td>
</tr>
<tr>
<td>WSS</td>
<td>Wearable sensors</td>
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<tr>
<td>ZC</td>
<td>Zero Crossing</td>
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Chapter 1

Introduction

1.1. Motivation

Gait analysis (GA) is the study of human gait. One of the fundamentals of GA is the human gait cycle, which splits human gait into a series of gait periods and gait events, which act as the boundary between the various periods. As a result, having systems that can automatically detect these periods and events is very beneficial for experts in this field. This process is called gait partitioning (GP), and has various applications in sports, rehabilitation, diagnostic settings [1].

In recent years, advances in gait analysis have provided many people with life changing technologies, like for example, functional electrical stimulation (FES) [2], and motorised prosthesis control (MPC) [3], which can help people with certain disabilities to perform tasks which would otherwise be difficult or impossible to perform and improve their life quality. However, there is much work yet to be done in this area before we can fully eliminate disabilities.

For these technologies to work effectively, they have to accurately keep track of the user’s gait cycle in real-time, so they rely on GP methods. GP has for a long time relied mostly on expensive, heavy and static equipment, but these tools are not suitable for the applications stated above, since they need to accompany the user throughout their daily lives and activities. For these reasons, researchers have taken an interest to wearable systems, such as footswitches and foot pressure insoles (FPIs); inertial measurement units (IMUs); and electromyography (EMG) sensors to perform GP [4].

Footswitches and FPIs are very cheap and accurate sensors, but they lack versatility due to their simplicity. They have low durability, and suffer from a lot of problems, like being unable to distinguish walking from non-walking activities, or not always being suitable for pathological gait applications. Also, due to their simplicity, these kinds of sensors are the easiest to analyse, not having the need for complex algorithms to provide useful information [1], [3]-[5].

IMUs are less accurate than footswitches but have a longer lifespan and are more versatile. They are capable of distinguishing walking and non-walking activities and are reliable in...
patho-logical scenarios. They are also more complex than footswitches and FPIs, often requiring the need for machine learning algorithms, but simpler rule-based algorithms can also be used to great effect with these sensors [1], [4], [6]-[8].

Finally, EMG sensors have the worst accuracy for detecting gait events and require complex machine learning algorithms to be able to perform but outperform other sensors at detecting gait onset and offset, intent recognition, proportional prosdissertation control, error correction and robustness to pathological gait. In other words, EMG sensors trade accuracy and simplicity for versatility, which give them much potential for GA applications [2], [9]-[11].

As a result, EMG sensors have been widely adopted for many gait partitioning applications, but their dependence on complex ML algorithms and their relatively low accuracy is still a problem that hinders progress in this area.

1.2. Goals

The aim of this dissertation is to develop a new machine learning algorithm for gait partitioning with EMG sensors. The algorithm must meet the following requirements.

- Function in real-time.
- Detect gait events within 125ms.
- Be able to distinguish walking and non-walking activities, so no false events are detected.
- Be robust to different environments such as slopes, stairs, load changes, etc.
- Be comfortable and not impair the user’s gait.

In many applications, such as diagnosis, sports and surgery planning, real-time performance is not a necessity, as information retrieved can be processed and analysed at a different time, without impacting the quality of the diagnostic. Real-time performance is crucial, however, for applications that require an action to be performed at a specific instant in the gait cycle, such as FES and MPC [12].

The interval between the detection of a gait event and its real occurrence is called “detection delay”, or simply delay. It has been shown that detection delays below 125ms are acceptable for MPC and FES, so the algorithm should detect events well-within this period [13], [14]. Delayed event detection leads to undesirable results and discomfort. In MPC, user of prosdissertation with delays higher than 125ms reported sluggish behaviour of the prosdissertation and showed overshooting problems and worse performance at performing simple tasks [14].

Being able to distinguish walking from non-walking activities is crucial in systems like FES and MPC. In these systems, an action is performed when a particular instance is detected by the algorithm. As a result, activities such as standing, sitting, shifting weight from one leg to the other, etc. should not be detected by the algorithm, since that would result in an undesired action, which could cause the patient to lose balance or even fall [6].

The algorithm must be robust to different environments, as the real world is constantly filled with slope changes and difficult terrain. A system that would only work on the user is walking on perfectly flat and level ground would not be suitable for real-world applications [15].

Lastly, the EMG system must be comfortable and not impair the user’s gait [16], as that would have the opposite effect to the pretended one, which is to improve the user’s comfort.
1.3. Dissertation Structure

This report is divided into 6 chapters: Introduction, Gait Analysis, State-of-the-art, Machine Learning, EMG, Conclusion.

2 - Gait Analysis

Chapter two will begin with an overview of gait analysis’ importance and various applications, and then will introduce the core fundamentals behind gait analysis, such as the gait cycle and the tools involved in gait analysis. After a brief introduction to the history of GA and the current rise of wearable systems, the concept of gait partitioning will be addressed, along with its applications in rehabilitation, sports and diagnosis. To finish off this chapter, the advantages of using wearable systems to perform GP are shown, especially for FES and MPC.

3 - State-of-the-Art

Chapter three describes the state-of-the-art GP methods that rely on wearable systems. In particular, the advantages and disadvantages of footswitches and FPIs, IMUs and EMG. At the end of chapter three, it is concluded that EMG is a versatile technique with great potential for GP but has a lower accuracy than other sensors and needs complex signal processing and machine learning algorithms to function as desired.

4 - Machine Learning

Chapter four will focus on the fundamentals of machine learning, the different steps involved in using machine learning for classification problems, such feature selection, feature extraction and algorithm evaluation, and the advantages and disadvantages of popular ML algorithms.

5 - Electromyography

Chapter five will instead provide an overview of electromyography, namely a basic description of how the EMG signal is produced by the human body, the difficulties of signal acquisition due to EMG signal’s random and noisy nature and the signal processing techniques used to try to mitigate said problems. After EMG signal is acquired and processed, features can be retrieved from the signal, making the original feature set.

6 - Conclusion:

The final chapter gives a final overview of the report, and suggests the future works.
Chapter 2

Gait Analysis

In this chapter we will review some fundamentals about Gait Analysis, including a summary of the history of gait analysis, a few applications and the recent outburst of wearable systems in this area. Then we will introduce and explain the concept of the gait cycle, events and periods, and give a brief overview of the function of relevant muscles for human gait. Other concepts such as EMG signal properties, acquisition and processing; and basic Machine Learning concepts and algorithms will also be presented in this chapter. Finally, the state-of-the-art methods in gait event detection will be presented at the end of this chapter.

2.1. Introduction to Gait Analysis

From an evolutional standpoint, Homo Sapiens is the only obligate bipedal primate, and this locomotion method is reflected in many human anatomical features, especially in the lower limbs and foot, which have evolved to maximise the efficiency of bipedalism [17].

Bipedalism freed the upper limbs from a paradigm of power grasping to a paradigm of human-like precision grasping, which is required for tool handling, and therefore of paramount importance in human evolution [18].

Even so, walking is seen as a trivial and mundane task, but the mechanisms of walking are extremely complex and require coordination between several different body mechanisms. The process begins in the motor cortex in the brain, the cerebellum is responsible for coordination of the muscles, the spinal nerves regulate the tension generated by the muscle fibres through feedback received from Golgi tendons and other proprioceptive receptors. In order to achieve the desired motion, the muscles must generate the appropriate amount of tension, the joints must have the correct range of motion and the bones must be robust enough to withstand the forces involved. Any abnormality in any of these systems, from the motor cortex to the bones, will probably result in an abnormal gait [9]. Furthermore, issues in different systems will trans-late into different gait pathologies, so gait analysis can be used to identify the root of the problem and lead to a more efficient treatment. More so, gait analysis can be used to assess the success of a hip replacement surgery, or, in some cases, even evaluate if surgery is neces-sary. In other cases, it can be used to prematurely diagnose certain neurological conditions that affect gait, such as Parkinson disease [1]. As a result, it comes as no surprise that human gait analysis has
sparked an interest in many researchers working in rehabilitation, diagnostic and athletics fields [19].

2.2. Fundamentals of Human Gait

So far this report has described why researchers have taken an interest in human gait, and the fruits of their labour. But what is human gait? How can researchers describe it and measure it? This section will attempt to answer those questions.

2.2.1. Gait Cycle, Gait Events and Gait Periods

Human gait is a cyclic process where muscles, nerves and senses all act together in unison to achieve a common goal: Bipedal locomotion. To better understand the motions involved and facilitate analysis, human gait is divided into gait cycles, which get subdivided into different repetitive movements, called “gait periods”. A gait cycle begins with the contact of one foot on the floor and ends when the same foot repeats that action [1], [4], and is usually divided into two phases - Stance and swing. The stance phase begins when the heel of the patient strikes the ground (heel strike - HS) and ends when the toe leave the ground (toe off - TO), and the swing phase begins when the foot leaves the ground and ends with the heel strike, repeating the cycle [1], [4], [15]. The problem with this approach is that it is dependent on two “gait events” to separate the gait phases, which becomes a problem when analysing pathological gait. Certain pathologies can cause a subject’s heel to strike the ground later than usual or after a different part of the foot, which invalidates that event as a trigger to the stance phase [1]. The solution for this problem is to divide these two phases into various periods, which allow the technicians a higher degree of precision. Since each period is the interval between two events, using a more granular model (more periods) will result in a higher probability of finding gait events which are unaffected by the pathology being studied, but these models will also be harder to analyse [4]. One of the most common gait models was introduced by the Rancho Los Amigos committee, which divides the gait cycle into 8 different subphases [19]. However, there are models which divide the gait cycle into any number of phases ranging from 2 to 8, and some even express the gait cycle in a percentage value, so it is up to the technician to decide which model is best suited to study a given pathology [4]. Some examples of gait models are show in figure 2.1.

<table>
<thead>
<tr>
<th>Granularity</th>
<th>Gait Phases</th>
</tr>
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<tbody>
<tr>
<td>Two Phases</td>
<td>Stance</td>
</tr>
<tr>
<td>Three Phases</td>
<td>First Rocker</td>
</tr>
<tr>
<td>Four Phases</td>
<td>Heel Strike</td>
</tr>
<tr>
<td>Five Phases</td>
<td>Flat Foot</td>
</tr>
<tr>
<td>Six Phases (a)</td>
<td>Loading</td>
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<td>Seven Phases</td>
<td>Loading Response</td>
</tr>
<tr>
<td>Eight Phases</td>
<td>Initial Contact</td>
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</tbody>
</table>

Figure 2.1 - Different Gait Cycle Models and their terminology from [4].

By analysing this figure, we can clearly see that there is no universal terminology in place, and often the same name applies to different concepts in different models. In order to avoid this confusion, we will use the terminology introduced in Vu et al. [15], shown in figure 2.1:
Vu et al. considers a gait model with 8 separate periods of gait, divided by 8 gait events. The gait events and periods identified by Vu are described below.

Gait events are single instance, usually used to mark the transitions between two gait periods. The gait events considered in [15] are:

1. Initial Contact (IC): This is the first moment when the reference foot touches the floor (usually with the heel) and marks the beginning of the Stance phase. This moment also marks the beginning first “double-support” moment since the opposite leg is also in its stance phase.
2. Foot Flat (FF): This is the moment when the reference toe touches the ground, so the foot is now fully in contact with the floor.
3. Mid stance (event): This is the moment when the COG of the patient is overtakes the heel of the reference foot.
4. Heel Off (HO): The moment when the reference foot’s heel leaves the ground.
5. Opposite initial contact (OIC): The moment when the Opposite foot makes contact with the ground, marks beginning of the second “double-support” moment.
6. Toe Off (TO): The moment when the reference foot completely leaves the floor. This moment marks the end of the Stance phase and beginning of the Swing phase.
7. Feet Adjacent (FA): The moment when the reference foot gets ahead of the opposite foot.
8. Tibia Vertical (TV): The moment when the reference tibia is in a vertical position.

Gait Periods are the periods in between two gait events. The gait events considered in [15] are:

1. Loading Response: The period between IC and FF, in this period the reference leg is loaded with the patient’s weight, hence the name. In typical gait, the knee is slightly flexed to absorb shock, and the heel is used as a rocker.
2. Mid Stance (period): Not to be confused with Mid Stance (event). While the foot is stationary on the floor (from FF to Mid Stance (event)), the body’s weight is shifted forwards, and the reference limb advances in relation to the foot.
3. Terminal Stance (TS): Similar to Mid Stance, but happens from Mid Stance (event) to HO. The body’s COG is pushed forward, getting ahead of the reference foot.
4. Push-Off: As the body’s COG overtakes the reference foot, the heel rises and the body rocks forward. The beginning of the second double-support moment marks the end of this period.

5. Pre-Swing (PS): Similar to TS but occurs after OIC. This is the second double-support period and lasts until the toe of the reference foot leaves the floor.

6. Initial Swing: Occurs between TO and FA, this is the first period of the Swing phase. To lift the reference foot of the ground, the hip and knee flex.

7. Mid Swing: Begins when both feet are adjacent. The hip reaches its maximum flexion during this phase.

8. Terminal Swing: After TV, the limb prepares for Loading Response. The hip and knee extend but the knee remains slightly flexed.

With this terminology, it is now possible to discuss different gait models and their uses in clinical settings. Please keep in mind that when discussing different models, the gait periods will not always match with this model. In these cases, we will define the gait periods as the moments between two gait events. It is also important to keep in mind that this model cannot be applied to certain pathologies which require their own gait models, but it can be applied to some abnormal gait cycles, such as Trans-tibial and Trans-femoral amputees’ gait.

2.2.2. Gait Muscle Activity

Walking is an extremely complex activity, which involves the coordinated activation and coordination of dozens of muscles. To put this matter into perspective, Vaughan, Davis and O’Connor [19] provide us with a graph of 28 of the main muscles involved in human gait plotting their activation levels against the percentage of the gait cycle (fig 2.2). Meanwhile, the same process, shifted by half a cycle, is repeating on the other leg. This type of analysis is important because it gives insight into the roles of muscles during the gait cycle and shows that muscle activity occurs in a cyclic, semi-predictable nature.

2.3. Gait Analysis History and Methodology

Section 2.2 described the fundamentals of human gait, namely the gait cycle, gait parameters and gait muscle activity. In short, it describes “what” gait analysis studies. This chapter will describe “how” researchers perform gait analysis, how the methodology evolved throughout the years and the real-world applications of this science.

2.3.1. Gait Analysis: How does it work? (Gait Analysis Methodology)

There are three main schools of thought in GA, but we must consider that these areas are not independent of each other and should be used together by clinicians to achieve the desired results. These schools of thought are kinematics, kinetics and muscle activity quantification.

Kinematics: Kinematics is concerned with studying the different movements involved in human gait. Usually, the subject’s body is divided into different segments, and each segment’s movement is tracked by a system of cameras. Markers are placed on specific body locations to facilitate the tracking of the segments. Then, a 3D rendering of the subject’s movement is obtained and placed in a coordinate system in order to be studied. This allows the user to gain knowledge about joint angles, joint angular velocities and joint accelerations, as well as the
positions, orientations and velocities of different body segments [20]. Nowadays, systems like VICON automate a great part of the process, making it possible to collect measurements just minutes after the arrival of the subject, but this was not always the case [16].

Gait kinematics has many uses in the athletics and clinical fields. For example, Robert M. Kay et. al., used a VICON system to find that when kinematic GA was performed in preoperative or-
thopaedic patients, experts would change their recommended treatment plan in 90% of the cases, and in 40% of cases the recommended procedures were deemed unnecessary after GA [21]. In addition, DeLuca Pa combined video data with EMG and force plate data to find that preoperative GA reduced the cost of surgery in patients with cerebral palsy [22].

Kinetics: In order to walk, muscle fibres must pull on tendons, which in turn exert torques on bone structures, which produce movement in the necessary body parts. With kinematics, only this final movement layer can be studied, but it is much more useful for a clinician to understand the underlying biomechanical forces responsible for the studied movements [23]. In fact, this was always one of the greatest goals of the early pioneers of GA [23]. This is where kinetics comes in, as it studies the forces and torques responsible for human gait. However, we cannot directly measure the forces from muscle fibres or tendons acting on the internal joints, so we must rely on indirect measurements [19]. According to Newton’s third law: “If you press a stone with your finger, the finger is also pressed by the stone.” [24]. In the same fashion, when we walk we produce forces on the ground and the ground responds with an equal, but opposite force, which is commonly called a “reaction force” (RF). Researchers have tried to measure these reaction forces since 1872, when M. Carlet developed a mechanism that could measure the forces applied on the foot. However, this primordial device only provided one-dimensional information, so much work was still needed to obtain the full three-dimensional RF [23]. Researchers in Germany were able to use kinematic data to estimate the three-dimensional reaction forces, but did not yet have the necessary tools to measure them directly [23]. Finally, in 1916, Jules Amar developed the world’s first device capable of measuring RF in all three dimensions, vastly improving on previous designs [23]. This was the early foundation of the modern force plate, the most powerful tool in a gait analyst’s arsenal and an indispensable tool in any GA laboratory. Amar’s design was gradually improved on, achieving better accuracy, reliability and simplicity. So, there is finally a system to reliably measure the ground forces, but what exactly can be achieved with this data? In the early days, obtaining the 3D ground forces was the main goal of investigators, although studying these external forces still does not shed light on the internal forces acting on the individual joints. For that, complex moment calculations were necessary so the limitations in computational power hindered progress in this area [23]. With advances in computational power, inverse dynamics approaches were used to successfully calculate the net moments and forces applied in the joints of the subject. Vaughan, Davis and O’Connor [19], describe this process in detail in [19]. Once the net internal forces and momentums of the joints are known, they can be applied in a variety of scenarios. From the designing of special braces to reduce the joint moments acting on certain joints to treat disorders like coxarthrosis [25], or for assessing normal or pathological gait [26].

It is important to understand that knowing the joint forces is not the same as knowing the individual muscles forces acting on said joints. There are often reciprocal forces acting on joints, where different muscles are simultaneously exerting abduction and adduction forces on the same joint in order to lock a joint in place [16], [19].

Muscle Activity quantification: We have seen how we can apply kinetics and kinematics to get an insight into the mechanisms of movement. However, these methods cannot show us the muscle activity of individual muscles. Kinesiological Electromyography (KEMG), on the other hand, uses surface or intramuscular electrodes to study the function of individual muscles and their effect on joint movement and gait cycle. This technique works by measuring motor action potentials produced by muscle tissue, but it is important to remember that this measurement is not a direct measurement of muscle tension.
The first recording of human electromyographic activity during voluntary contraction was performed by Emil du Bois-Reymond in 1849, sparking the age of electromyography. However, it wasn’t until the 1940s that this technology started being used to study dynamic movement [27]. In the 1960s, EMG was already being used to treat a variety of specific disorders in clinical settings. Hardyck [28] recorded laryngeal muscles activity to detect subvocalization while reading. If subvocalization was detected, the subjects were given an auditory stimulus. As a result, subjects quickly stopped subvocalizing, which had a positive impact on their reading development. In the following decades, EMG was used as a way to plan surgical interventions in children with cerebral palsy, such as tendon transfers [29], [30]. Muscles which showed continuous activity during walking had their tendons lengthened, which decreases muscle stiffness and spasticity, resulting in an improved control by the patient [30].

Nowadays, EMG provides a fast, cheap and non-invasive way to simultaneously monitor multiple muscle activities, and this allows practitioners to visualize hidden synergies between muscles, especially during complex activities such as walking or running [28], [19], which in turns provides the practitioner with a much more intuitive sense of the role of each muscle during a specific activity. Although EMG does not directly provide a measurement of muscle contraction force, there have been studies that attempt to estimate muscle force from EMG signal [31].

2.3.2. Wearable Systems in Gait Analysis

We have talked about the early methods utilized in GA, and their shortcomings. It is a common theme that many GA approaches rely on bulky, expensive and immobile equipment. Force platforms and Image Processing Systems use what is commonly called “non-Wearable Sensors” (NWS). NWS tests are performed in controlled environments such as laboratories where the equipment is permanently set. The advantage of these methods is that they are less vulnerable to random variability in their data acquisition, since they are less vulnerable to external variables, and as such achieve higher accuracies. On the other hand, these methods are more expensive than their wearable counterparts, since they need to be carefully installed and calibrated and usually require expensive equipment and trained technicians to operate. Another disadvantage of these methods is that subjects cannot be regularly monitored performing their day-to-day activities, but only during short sporadic tests, which may not be representative of the subject’s true condition, and some movement restrictions are applied to the subject. Even so, the gold standards in GA are still NWSs for their superior fidelity [1], [4].

Currently, the focus is starting to shift towards light, wearable sensors (WSs). This will mean that laboratories do not need to invest such large sums of money into expensive equipment, and setup and calibration routines will be simplified. But the biggest advantage of WSs is that they allow measurements to be taken in a larger array of scenarios and environments, including everyday activities where a clinician cannot be present. Some wearable sensors can even store data to later be reviewed by clinicians [1], [4].

For example, accelerometers and gyroscopes can be attached to the patient’s body to perform kinematic measurements, by tracking both linear and angular accelerations of different body parts, respectively. In addition, magnetoresistive sensors can be used to calculate the 3D orientation of a body segment. These three sensors are typically combined into inertial measuring units (IMUs), which are more accurate than the individual sensors. Goniometers can be used to determine angles between body segments and subsequently the angular velocity of joints such as the knee [1], [4].
As for kinetics, researchers regularly use footswitches and pressure insoles. Footswitches are very basic pressure sensitive devices, which are placed on the sole of the foot, often in pairs or groups. They can be used to accurately detect foot contacts with the ground, but they suffer from a short lifespan and are unable to provide information about ground reaction forces. Foot pressure insoles behave like footswitches, except they record information about the entire foot surface in contact with the floor. This allows them to measure more useful information such as vertical ground reaction forces [32], [4]. Some foot pressure insoles have tried to measure 3D GRFs, although with limited success. For this reason, to perform the full measurement of 3D ground reaction forces, force platforms are still the only technology available, so they are still required for certain applications such as calculating the internal joint forces and momentums.

Muscle activity quantification systems already rely on EMG electrodes, which are a wearable technology. Chapter 4 will provide a brief overview of EMG.

As with any technology, WSs also have disadvantages in a GA setting. WSs are less accurate than their non-wearable counterparts; require the use of batteries, which can restrict their performance; and are more prone to interference and noise. Also, WSs biggest strength of being able to be used outside of a laboratory setting can also be seen as a weakness, since it is not possible to check if the data obtained in an uncontrolled environment was affected by external factors [1], [4]. As such, it is up to the researchers to analyse each situation carefully and use decide which kinds of sensors should be used. This will depend greatly on the parameters being analysed and the error which the researchers are willing to tolerate.

2.4 - Introduction to Gait Partitioning

So far, this chapter has introduced the basics of the gait cycle, and the basics of gait analysis. By using gait analysis techniques to study the gait cycle, we introduce the concept of gait partitioning. This section will provide a brief explanation of gait partitioning applications and methodologies.

As we know, the gait cycle is divided into periods, which are determined as the intervals between specific gait events. Gait partitioning is the process of accurately determining gait events and periods by analysing kinetic, kinematic and muscle activity quantification data. With accurate gait partitioning, researchers can [1], [2], [4], [15], [31], [33]-[35]:

- Evaluate gait recovery of patients after surgical interventions or physiotherapeutic treatments.
- Classify various daily activities.
- Perform early diagnosis and track the progress of neurodegenerative or systemic diseases which impact gait.
- Assist in professional coaching.
- Electrically stimulate muscles (FES) in a controlled manner to assist patients with pathological gait.
- Assist and monitor the recovery of stroke patients.
- Develop control strategies for powered prosthetics to assist in the recovery of lower limb mobility.

Gait partitioning can be performed with a variety of sensors, both wearable and non-wearable. Each sensor has its own strengths and weaknesses. For example, force platforms are the gold standard for detecting IC and HO events [4], [36], [37], [38], because of their accuracy, but cannot be used to detect other events [4]. Video systems such as VICON can be used to detect all 8 gait events [2], [39], with great accuracy, and are seen as the gold standard for high granularity models, but their use is limited to laboratories and cannot be implemented for daily applica-
tions [4]. For example, FES and prosthetics control are two applications that are must be active throughout the patient’s daily life, so cannot rely on non-wearable sensors. As a result, researchers have tried to use wearable sensors, already in use for other gait analysis purposes, to perform gait partitioning. The next chapter will present a brief overview of the state-of-the-art methods in gait partitioning with wearable sensors.
Chapter 3

State-of-the-Art

It is difficult to compare gait partitioning methods since there is not a standardised metric to evaluate these methods. Some papers use accuracy of gait classification, others use time delay between the tested method and a control in milliseconds, and some even express this difference in percentage of the gait cycle [15]. Depending on the problem at hand, different applications can be more suitable than others. For example, for control of powered prosthetics, online classification of data is necessary, and time delays for detection of IC and TO must not exceed 125ms [14]. In other applications such as diagnosis, offline classification can be enough to provide useful information [40] although more granularity may be required [41]. In this chapter, we will provide a brief overview of some of the main techniques used for gait partitioning, namely footswitches, IMUs and EMG, and discuss their advantages and disadvantages. This chapter will focus mainly on IC and TO detection delays, in order to have a fair comparison between the different methods.

3.1. Gait Partitioning Methods

Section 2.3.2 gives a brief description of wearable sensors commonly used in GP, in particular footswitches, pressure insoles, IMUs, accelerometers and gyroscopes, and EMG. This section will describe how these sensors are applied to GP problems, and present their advantages and disadvantages, which will then be compared in section 3.2.

3.1.1. Footswitches and foot pressure insoles

Many researchers showed that footswitches can detect IC and TO almost as accurately as force platforms [3], [4], [36]. Although they are unable to identify periods in the swing phase, some studies using footswitches achieved granularities as high as six gait periods, although this resulted in lower accuracies than studies using lower granularity models [42].

Balbinot [5], describes the use of two low-cost piezoelectric footswitch sensors located at the heel and toe to detect IC and TO with delays of $(16\pm1)$ ms and $(20\pm9)$ ms respectively, in relation to force plates, which is consistent with literature values [12].
Cherelle [3], used a 4 period model to control a powered lower limb prosthesis. Their system used two Force Sensing Resistors (FSR), one placed at the “heel” and another at the “toe” of the prosthesis, to detect 4 gait events: Initial contact, Foot Flat, Heel off and Toe off. Their method divided the gait cycle into 3 stance periods: IC to FF, FF to HO and HO to TO; and 1 swing period: TO to IC. The footswitches had an active and inactive state, indicated by a pressure threshold. By checking the active state of the heel and toe resistors, it is possible to know in which period the patient is currently and control the prosthesis accordingly. For example, in the IC to FF period, an actuator contracts a spring, which is then released on the push-off period, from HO to TO.

In conclusion, footswitches are very cheap and accurate for low granularities. Besides, they require very simple algorithms to perform gait partitioning, in comparison to other techniques [5]. In some cases [3], [43], a basic threshold level is sufficient to achieve adequate results. However, footswitches are unable to reach granularities higher than 6 gait periods, and, most importantly for applications like FES and prosthetics control, they are sensitive to disturbance by non-walking activities. Activities like sitting, standing, shifting weight from one leg to the other, sliding feet, etc., could trigger the sensors, leading to unwanted consequences [6]. Furthermore, their low durability is another known problem of these sensors and their success with pathological gait is limited [8], [44]. Foot pressure insoles work with the same principles as footswitches, so they suffer from the same problems [4], although they avoid the additional problem of sensor positioning, which is difficult on patients with abnormal gait and can lead to poor results [44], [12]. Overall, Footswitches and FPIs have good accuracy for gait partitioning, but are limited in their applications due to their disadvantages.

3.1.2. Inertial Measurement Units

IMUs consist of accelerometers, gyroscopes and sometimes magnetometers, which when combined provide information about the IMUs’, translation and rotation on three axes, which in turn, provides information about the body part the IMU is attached to. Unlike footswitches and FPIs, IMUs can detect periods of the swing phase of the gait cycle, and thus can be used to identify all 8 phases of gait [4]. IMUs are also more forgiving in their placement, when compared to footswitches and EMG sensors [15] [6].

Maqbool et al. [45] used a single shank-mounted inertial measurement unit (IMU) consisting of a 3D accelerometer and gyroscope to detect IC, FF, HO and TO. The data from the IMU was fed to a rule-based algorithm, and gait event detection delay was measured in relation to footswitch sensors. Results for transfemoral amputees are shown in table 3.1:

Mannini et al. [6] utilized a single IMU attached to the foot to detect IC, FF, HO and TO. For this study, only acceleration data from the IMU’s gyroscope was fed to a Hidden Markov Model algorithm. Event detection delays in relation to a reference VICON system are presented in table 3.1. This study also reported that exact sensor placement is not necessary to achieve better results and that the algorithm was robust to weight shifting and load changes.

Finally, Müller et al. [46] used a single IMU, containing 3D accelerometers and gyroscopes to the instep of a shoe. Müller was able to detect 4 gait phases using a rule-based algorithm, but only reported timing delays for IC and TO, which are shown in table 3.1. Like Mannini et al., Müller et al. found that the IMU provided satisfying results, even without exact placement.
In conclusion, IMUs have slightly worse accuracy than footswitches, but overcome many of their disadvantages, by being durable, easy to mount on different body parts and able to detect all phases of gait [15].

Table 3.1 - Gait event comparison between Maqbool et al., Mannini et al. and Müller et al. [6], [45], [46]. Timing delays are presented in average delay + standard deviation, in milliseconds. Negative values mean the event was detected by the IMU system before the reference system.

<table>
<thead>
<tr>
<th>Gait Event</th>
<th>Maqbool et al.</th>
<th>Mannini et al.</th>
<th>Müller et al.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Contact</td>
<td>21.8 ± 20</td>
<td>62 ± 47</td>
<td>100 ± 50</td>
</tr>
<tr>
<td>Foot Flat</td>
<td>-153 ± 103</td>
<td>-3 ± 53</td>
<td>-</td>
</tr>
<tr>
<td>Heel Off</td>
<td>114 ± 60</td>
<td>86 ± 61</td>
<td>-</td>
</tr>
<tr>
<td>Toe Off</td>
<td>-7.5 ± 15.5</td>
<td>36 ± 18</td>
<td>50 ± 70</td>
</tr>
</tbody>
</table>

3.1.3. Electromyography (EMG)

EMG sensors, like IMUs, can be used to detect all 8 gait periods, but have lower accuracy than other GP sensors. Nevertheless, these sensors have plenty of advantages which make them suitable for GP and so have been widely used for this purpose, especially in FES and MPC applications [2], [31], [39], [47]. There is a lot of variability in classification studies using EMG. Electrodes can be placed in different muscles, the features selected for training the algorithms can be different, as can the actual ML algorithms used. For example, Bayesian Information Criteria [39], Linear Discriminant Analysis [48], Artificial Neural Networks [49], Fuzzy Inference Systems [2], [34], Stacked Sparse Autoencoders [48], and Hidden Markov Models [50], have all been used to perform classification problems with EMG signal.

Nazmi et al. [49] used EMG signal from tibialis anterior (TA) and gastrocnemius medialis (mGas) to detect IC and TO events in healthy gait. The acquired EMG features - RMS, SD, MAV, IEMG, and WL - were fed to an ANN comprised of three layers with one input neuron for each feature, two output neurons for gait phase classification and 10 neurons in the hidden layer. Footswitch data was used as the control to measure the delay of the ANN classification. IC and HO events were correctly classified 87.5% of the time. Of these 87.5% occurrences, the average time differences between ANN and footswitch data was 35 ± 25 ms for IC and 49 ± 15 ms for TO. Although the study showed promising results, the testing dataset consisted of only one patient, only two muscles were analysed, and the authors admit the use of footswitch sensors is not the most robust method for detecting IC and TO. Having data from more muscles would increase the dimensionality of the classification problem, but it could also lead to more reliable classification, and according to the authors, the use of force plates to detect IC and TO events could also lead to more robust results.

Joshi et al. [39] used EMG signal from the Gastrocnemius, tibialis anterior, bicep femoris and quadriceps femoris to classify the normal gait cycle into 7 phases. This study used MAV, WL, variance and 4 AR coefficients to train an algorithm which used a combination of Bayesian information criteria (BIC) for feature selection and LDA for classification. Unfortunately, the study does not show the average time differences of individual gait event detection between the EMG classification technique and the VICON based technique used as the control, but it achieved an overall classification accuracy of 76 ± 13 ms across the whole gait cycle. Although these results do not look too promising compared to others in literature, it’s im-
important to keep in mind that classifying 7 separate periods of gait is a more demanding problem than classifying only 2 periods.

Finally, Lauer et al. [2] used an adaptive neuro-fuzzy inference system (ANFIS) to detect seven gait periods in seven children with cerebral palsy. EMG signal was acquired from the left and right vastus lateralis muscles. Acquired signal was sampled at 1.2 kHz and bandwidth filtered from 20 to 350 Hz. From this signal, only raw values from both muscles and their respective derivatives were fed to the ANFIS algorithm. Timing delays were measured in relation to a VICON system and are shown in Table 3.2. An interesting characteristic of this study was that the evaluation of the algorithm was performed a second time, with the same children, two months after the original evaluation, to check if the repeatability of the algorithm over time. These results are also shown in Table 3.2

Table 3.2 - Timing delays between ANFIS and reference VICON system. 2nd Validation data was collected two months after 1st Validation to test the repeatability of the algorithm [2]. Timing delays are presented in average delay ± standard deviation, in millisecond. Negative values mean the event was detected by ANFIS before VICON.

<table>
<thead>
<tr>
<th>Gait Event</th>
<th>1st Validation</th>
<th>2nd Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Contact</td>
<td>4 ± 40</td>
<td>18 ± 38</td>
</tr>
<tr>
<td>Midstance</td>
<td>16 ± 64</td>
<td>5 ± 61</td>
</tr>
<tr>
<td>Heel Off</td>
<td>-12 ± 50</td>
<td>-3 ± 49</td>
</tr>
<tr>
<td>OIC</td>
<td>-7 ± 37</td>
<td>-2 ± 35</td>
</tr>
<tr>
<td>Toe Off</td>
<td>-5 ± 31</td>
<td>-12 ± 36</td>
</tr>
<tr>
<td>Feed Adjacent</td>
<td>-12 ± 45</td>
<td>-20 ± 55</td>
</tr>
<tr>
<td>Tibia Vertical</td>
<td>29 ± 44</td>
<td>19 ± 42</td>
</tr>
</tbody>
</table>

So, from this study, it can be concluded that EMG shows good repeatability and adequate accuracy for performing GP. It also shows that EMG can be used with patients with pathological gait. However, the ANFIS algorithm did not perform classification in real-time, which makes this system unsuitable yet for real-world applications. In the next section, we will further discuss the advantages and disadvantages of EMG for GP problems.

### 3.2. Advantages and Disadvantages of EMG

EMG allows the classification of eight gait periods, the highest granularity used in gait analysis, only matched by IMUs [4] and video systems. However, EMG signals are very sensitive to noise, and so require higher complexity in signal acquisition and processing. EMG based methods also usually achieve lower accuracies than methods such as footswitches or IMUs and utilize more complex algorithms to perform gait analysis. However, there are some areas where EMG goes above and beyond other GP systems, especially in areas which are useful for powered prosthetic control and FES applications. Below are listed some of the main reasons why EMG was chosen in this dissertation to perform GP.

Firstly, EMG has the potential to predict human movement before it occurs, making it useful for detecting gait onset and offset [31]. This was confirmed by [51], where EMG detected gait initiation in transfemoral amputees between 63 and 138 ms prior to inertial sensors.
Secondly, EMG can differentiate between gait and non-gait activities [6]. This means that EMG will not detect false positive events, such as sitting or shifting weight from one leg to another. A false positive could lead to a loss of balance or even a fall, which would be an unacceptable risk in real-life applications.

Furthermore, EMG has better error correction potential than footswitches. In instances where gait events where not correctly identified by EMG, the error was at most resolved by the following gait event, as opposed to the use of footswitches, where errors were only detected and resolved by the next gait cycle [52].

Lastly, EMG has the ability to actively control the torque output of prosthetics, making it far superior to other systems that do not possess that ability. In fact, [10] showed that patients utilising footswitch controlled prosthetics showed worse walking patterns and higher muscle activation levels compared to subjects using proportional myoelectric controlled prostheses, going as far as labelling footswitch controlled prosthetics as a hindrance to patients. Their results were later confirmed by Pauw et al. [43], who showed increased metabolic costs in patients using the footswitch-controlled Ankle Mimicking Prosthetic Foot prototype 4.0.

### 3.3. Final Remarks

The objective of this chapter was to explain the main differences between the different wearable sensors used in GP, their strengths, weaknesses and performances. Examples of studies were presented for each type of sensor, to provide some insight into the different methods used by researchers to obtain gait event timings from sensor data, and compare results obtained with different kinds of sensors. One problem of this approach was the lack of a standardised metric to evaluate the success of the sensors. So, to finish this chapter, we present a comparison of time delays between the detection of IC and TO, using the different methods. All timing delays presented in table 3.3 were referenced either to VICON systems or force plates, to ensure a fair comparison between the values.

<table>
<thead>
<tr>
<th>Gait Event</th>
<th>Footswitches</th>
<th>IMUs</th>
<th>EMG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Contact</td>
<td>16±1</td>
<td>62 ± 47</td>
<td>4 ± 40</td>
</tr>
<tr>
<td>Toe Off</td>
<td>20 ± 9</td>
<td>36 ± 18</td>
<td>-5 ± 31</td>
</tr>
</tbody>
</table>

From this table, we can see the accuracy of the footswitches in relation to the other two methods, and that IMUs and EMG present similar accuracies. Even so, this dissertation will focus on the potential of EMG due to the advantages described in section 3.2.
Chapter 4

Machine learning

This chapter will provide a short explanation of what is Machine Learning and why it can be used to detect gait events from EMG data. Then, the fundamental concepts of machine learning, such as feature selection and extraction and overfitting, are described, as well as how the algorithm’s performance is evaluated. Finally, some examples of ML algorithms will be pre-sented, along with their strengths and weaknesses.

4.1. Introduction to Machine Learning

Machine Learning is a term which denotes an algorithm that has the capability to auto-matically process large amounts of data, retrieve useful information from said data, and apply the information to perform a particular task. One of the tasks ML algorithms excel at is classification problems, such as the detection of gait events from EMG data [34].

A classification algorithm is tasked with labelling an instance with a particular “class” and can be deductive or inductive. In deductive problems, the rules that define the different classes are known, and the ML algorithm is tasked with applying those rules to a particular instance to determine the class of that instance. In inductive classification, the classification rules are not known, and must be estimated by the algorithm, by analysing different instances. In other words, deductive problems process from the general to the specific and inductive problems from the particular to the general [53].

Another way to describe ML algorithms is by their learning method. Supervised learning uses previously labelled instances, so the algorithm knows what class it should be outputting for a particular instance. Unsupervised learning uses unlabelled instances and is used when research-ers are looking for new classes with which to label said instances. In Reinforced learning, a “trainer” provides the algorithm with a scalar feedback about its performance, and the algo-rithm follows the actions that maximise this scalar feedback to maximise performance [53].

In the case of gait event detection with EMG, the classification rules are not known, but data can be labelled by a reference system, like force plates or a VICON system. This means that the classification algorithms best suited for this problem are supervised induction algo-rithms. In this report, a classifier will refer to a supervised induction algorithm [53].
As stated, induction algorithms are fed a large amount of data (training set) and must “learn” how to automatically label new, unseen data (testing set). Since induction algorithms learn from data, it is very important that the data used to train the algorithm is reliable and fit for the purpose at hand. Data is considered “unreliable” if one of the following circumstances applies [53]:

- There is noise in the data.
- The data has missing values.
- The curse of dimensionality.

Fortunately, there are methods that can be used to counteract these problems. Pre-processing techniques, such as the use of filters, can minimize the “noisiness” of data or other techniques can be used to measure the “noisiness” of data to check if it is suitable to be used by the classifier, and missing values in many cases can simply be ignored [53].

In addition, feature selection and feature extraction are techniques used to reduce the dimensionality of a problem. Every additional feature introduces a new dimension which exponentially increases the complexity of a problem [54], so in certain scenarios it is not possible to employ the entire feature set obtained from data acquisition in the machine learning algorithm.

Feature selection and extraction solve this problem by creating new and smaller feature subsets that will be used to train the algorithm, instead of the initial feature set. Having less redundant and irrelevant data allows the algorithm to function faster and more accurately. In fact, using a proper feature subset is the most important factor in training a classification algorithm [55].

4.2. Feature Selection

We have discussed that using too many features will negatively impact the performance of the algorithm, so from the available features, we must select which ones should be kept. The features that are kept are part of what is called the “feature subset”. If we have \( n \) features, we can obtain \( 2^n \) feature subsets. It is simply not practical to test and compare all \( 2^n \) subsets, so other methods must be used to obtain a feature subset that gives the classifier a good accuracy [56]. We want the feature subset to have as few features as possible, but how do we go about selecting which features should be fed to the algorithm and which should be scrapped? The first, more subjective method, is to rely on experts in the field of the problem to indicate which features are more informative [53]. Alternatively, one can use the wrapper or filter methods to perform feature selection [55].

4.2.1. Filter Method

The filter method is essentially a pre-processing step. It creates a set of criteria that the features must meet. The features that do not meet these criteria are eliminated and the ones that do are passed on to the algorithm [57]. For example, the user can specify that only features with a variance above a certain threshold, or only the \( k \) features with the higher variance can be used to train the algorithm, based on the intuitive assumption that features that do not show a lot of variance also do not introduce a lot of new information. Likewise, we can measure the correlation between features and specify a correlation threshold. Features that
correlate too much with other features introduce redundant information and so can be removed [55].

The advantage of filter methods is that they are very easy to implement, require very low computational power and are based on an intuitive understanding of the algorithm. However, they do not take into account the classifier’s performance, they simply evaluate the intrinsic properties of the features to accept or delete them based on subjective criteria [56]. Another disadvantage is that the criteria used in filter methods must be manually set, i.e. thresholds, and the wrong criteria can result in poor results for the classifier [57].

4.2.2. Wrapper Methods

By contrast, the wrapper methods do take into account the classifier’s performance, resulting in much higher accuracies than filter methods. However, these methods are much more computationally heavy than filters and are prone to “Overfitting” [56], a concept we will discuss ahead. The main steps in wrapper methods for feature selection are shown below:

![Figure 4.1 - Wrapper methods work pipeline. Adapted from [56].](image)

There are three main philosophies in wrapper methods: complete search strategy, heuristic search strategy and random search strategy.

**Complete search**

Complete search algorithms compare different feature sets until the best solution (global optimum) is found. For example, the “Branch and Bound” algorithm introduced in [58] tries to find the optimal subset of size $m$ from a set of $n$ features. If we have 24 features, and want a subset of size 12, there are $2^{24} = 2,704,156$ possible combinations, which would be impossible to test, but the branch and bound algorithm only needs to evaluate 6000 combinations to reach the global maximum, so how does the algorithm achieve this? The algorithm is able to do this by first assuming that the selection criterion function, which we want to maximise, satisfies monotonicity, meaning that if we have a particular combination of features, removing more features from this combination will give the selection function a lower value. Without going into detail, this is how the algorithm works for $n=6; m=2$: in order to select 2 features, the algorithm must delete 4 ($6-2=4$).

Let each element in $\{1,2,\ldots,n\}$ represent one of the $n$ original features, and $(Z_1,\ldots,Z_p)$ be the removed $p = m-n$ features. Then $(Z_1,\ldots,Z_p)$ is a solution to the problem, by telling us which features to delete. Now we introduce the selection criterion function $J_p(Z_1,\ldots,Z_p)$. The best possible solution is the one that satisfies the condition:

$$J_p(Z_1,\ldots,Z_p) = \max J_p(Z_1,\ldots,Z_p)$$  

(1)
Monotonicity guarantees us that:

\[ J_1(Z_1) > J_2(Z_1, Z_2) > \ldots > J_p(Z_1, \ldots, Z_p). \]  

(2)

The algorithm then generates a solution tree, and greedily follows the node for which \( J_i \) is highest, until it reaches the final level (level \( p \)). \( (Z_1, \ldots, Z_p) \) is the first solution. \( J_p \) is computed and stored as \( J_o \) (J optimal), and \( (Z_1, \ldots, Z_p) \) is stored as \( Z_o \). Now the algorithm explores other branches of the solution tree, using the same greedy method. If a node has \( j_i < j_o \), we can conclude from (Equation number) that:

\[ J_o(Z_1, \ldots, Z_p) > I_i(Z_1, \ldots, Z_i) > J_{i+1}(Z_1, \ldots, Z_{i+1}). \]  

(3)

This means that \( (Z_1, \ldots, Z_i) \) and every node subsequent to it will have a criterion value below \( J_o \), and so can be ignored. This is the reason why the algorithm can find the global optimal by only analysing a fraction of the possible feature sets. If the algorithm reaches the final level again, the current \( J_p \) is compared to \( J_o \). If:

\[ J_p(Z_1, \ldots, Z_p) > J_o \]

(4)

\( J_p \) is stored as \( J_o \), and \( (Z_1, \ldots, Z_p) \) as \( Z_o \), and the algorithm continues exploring other branches. Otherwise, \( J_o \) and \( Z_o \) remains the same and the algorithm continues as previously. When all the nodes have been explored, the algorithm stops, and \( Z_o \) is the best possible solution for \( n \) feature selection.

Complete search algorithms, although being very simple and providing global optimum solutions, suffer from exponential complexity, meaning a small increase in the number of features will massively increase the amount of time needed to compute the answer [56]. Furthermore, they require the selection criterion to meet certain requirements, such as monotonicity [55], [58].

**Heuristic search**

Heuristic search algorithms rely on guesses, estimates and approximations to solve problems. As a result, a heuristic solution will rarely be the best possible one but can still be adequate to tackle many problems [56].

Forward Selection and Backward Elimination are examples of heuristic search algorithms. In forward selection, we begin with an empty feature subset and start by “feeding” the algorithm the features, individually, and checking the outputs of the algorithm. The feature that provides the most desirable output is added to our feature set. Then, the process repeats, adding one more feature to the feature subset, until the algorithm’s performance is satisfactory. Backward elimination applies the same principle backwards, meaning our initial feature set contains all available features, one feature is removed before running the algorithm and checking the output. This process is iterated until we find the feature that, once removed, has the least negative impact on the algorithm’s performance and so this feature is removed from the feature set, and the process repeats until the algorithm’s performance is satisfactory [56].

Heuristic search methods should not be used when one is concerned with achieving the global optimum solution, due to their often trial-and-error and greedy nature. However,
these methods will reach a global minimum solution in a very short amount of time and with low computational power, and so can be used if a local optimum solution is adequate, or if finding a global optimum solution would be deemed too time-consuming [56].

**Random Search**

Random Search methods escape being trapped in local solutions by introducing a randomizing effect. However, many parameters must be set to ensure that the randomizing effect is not too strong or weak, meaning their success is dependant on many factors. Examples of random search methods are Genetic Algorithms (GA), Simulated Annealing and Particle Swarming Optimization [56].

A Genetic Algorithm mimics biological evolution to optimize a solution. The way this algorithm works for feature selection is as follows [59]: all $n$ available features are put in a binary vector $[f_1,f_2,...,f_n]$, where $f_i$ can have value 1 - indicating that $f_i$ is active - or 0 - indicating $f_i$ is inactive. For example, for $n=4$, the vector $[0,1,0,1]$ means feature $f_2$ and $f_4$ are active. In the first step, the GA creates the first population of $m$ randomized vectors. The system evaluates the classifier with each feature vector in the population and selects the best ones based on a survival criterion. The next step is called the “crossover”, where the best vectors are paired and produce “offspring”, a new population with the best characteristic of the previous population. In this step, “mutations” can also occur, which randomly modify the offspring. Over many generations, the population will evolve into one that maximizes the survival criterion, reaching a global optimum solution for the feature selection problem.

Random Search methods are usually slow and computationally heavy. Furthermore, they require a big set of parameters (Survival criterion, mutation rate, and initial population for GAs) to be finely tuned in order to achieve a desirable result, otherwise the algorithm can get trapped in local optimums, or not converge to a solution at all. So, although these algorithms can find global optimum solutions, this process is slow and not always guaranteed. In addition, random search algorithms are the most prone to suffer from Overfitting [56], [59].

**4.3. Feature Extraction**

In feature extraction, instead of choosing features from the original feature set, we produce new features from the original feature set [55]. Creating new features may seem counter-intuitive when tackling the problem of dimensionality but when a problem contains many features, it is likely that some features will contain redundant or irrelevant information. Feature extraction is used to combine the relevant information of several features into a smaller pool of features, by eliminating redundancy and irrelevant information. This results in an overall reduction of the dimensionality of the problem, without much loss of critical information about the original signal. Two examples of feature extraction are principal component analysis (PCA) and linear discriminant analysis (LDA). PCA is considered one of the most powerful dimensionality reduction techniques but does not take into account the classes of the data points, which can lead to clustering and poor classification. LDA on the other hand, takes into account classes, making it extremely useful for classification problems, but it can only be used with labelled data [54].
4.3.1. Linear Discriminant Analysis

Linear discriminant analysis is an extremely useful extractor in supervised classification problems because it guarantees maximum separability between classes [60]. Suppose we have a labelled classification problem with 2 classes and \( n \) features or dimensions. It is possible to project the data points in the \( n \)-dimension hyperspace onto 1 axis, therefore reducing the dimensionality of the problem. LDA finds the axis that maximises separation of the two classes.

The new axis is created according to two criteria: After the data is projected onto the new axis, the distance between the means of the two classes \( (\mu_1 - \mu_2) \) must be maximised and simultaneously, the variance within each class (\( s_1^2 \) and \( s_2^2 \)) must be minimised. These two criteria are joined to create the Fisher’s Criteria [61], or separation equation:

\[
W = \frac{(\mu_1 - \mu_2)^2}{s_1^2 + s_2^2}
\]  

(5)

Where \( (\mu_1 - \mu_2)^2 \) represents the variance between classes, and \( s_1^2 + s_2^2 \) represents the variance within classes. The difference between the means of the two classes is squared to avoid negative values. Since we want to maximise variance between classes and minimise variance within classes, we need to find the axis which maximises \( W \).

Now that the new axis has been found, our \( n \)-feature dataset can be represented in only one dimension, which means that, by creating a new feature, the dataset’s dimensionality has been reduced. The process remains semi-identical for a higher number of classes, but instead of creating one new axis, more axes can be created. For a \( k \)-class problem, the maximum number of axis that can be created is \( k-1 \).

Although LDA implies some loss of information, it preserves class-discriminatory information, which is the kind of information that is most relevant for classification problems [62].

4.4. Algorithm Evaluation

When describing the different feature selection methods, all FS algorithms shared a step where they must analyse the classifier’s performance. A classifier’s performance can be evaluated in multiple ways. The simplest way to do so is to split the complete dataset into separate training sets and testing sets. After the ML algorithms learns from the training set, it can be run on the testing set. Afterwards, classification parameters such as accuracy, sensitivity, specificity, error rate, ROC AUC, etc, can be measured [63]. Other parameters such as speed and robustness (how sensitive the algorithm is to noise) can also be used if they are deemed important [53], [57].

However, a more reliable way of estimating the classifier’s performance is to use k-fold cross-validation [64], [65]. In this method, the original training set is further split into \( k \) folds \( (F_1, \ldots, F_k) \). Then, copies of the original training set are created, until there are \( k \) identical training sets \( (S_1, \ldots, S_k) \) and every training set \( S_i \) is split into training and validation sets, according to this rule:

\[
\text{for } i \in (1,k), \ F_i \text{ will be the validation fold in set } S_i.
\]

This process is visually explained in figure 4.2.
Figure 4.2 - K-fold cross-validation method for algorithm evaluation.

For every set $S_i$, the chosen classification parameter ($C_i$) is evaluated, and the average of these parameters is calculated to obtain a better estimate of the classifier’s performance. When the classifier’s performance is deemed satisfactory, for example when the classification parameter $C$ surpasses a predefined threshold, the classifier is tested on the independent test set to obtain a more representative estimate of the classifier’s performance [53], [57].

4.5. Overfitting

Overfitting is a problem that occurs when the inductive classification algorithms works “too well”. As was explained, an inductive classification algorithm learns from the training set to inductively create a general set of rules that classify new data. If the set of rules matches too closely with the training set, the algorithm is said to have low predictive power [57]. Overfitting can happen for a number of reasons, namely if the algorithm is more complex than what is necessary, or if it has become too specialized on the training set by learning for too long. Figure 4.3 shows how overfitting affects the algorithm’s accuracy. As the algorithm becomes over-specialised on the training (validation) data, it can classify the validation set better, but loses the ability to correctly classify unseen data [54], [57].

There are, however, ways to reduce the risk of overfitting, such as using cross-validation techniques to evaluate the classifier’s performance, using a model that is complex enough to model the problem (fig. 4.3) - but not too complex to induce overfitting - or using a “stopping criterion”. A stopping criterion tells the algorithm when to stop training, so it does not have time to become over-specialised on the training set [57].

There is a large number of machine learning techniques used for EMG signal classification. Artificial Neural Networks [49], [48], [66], Hidden Markov Models [50], Fuzzy Inference Systems [2], [34], K-nearest neighbour [67], Random forests and decision trees [67], and others. As expected, different algorithms will have different strengths and weaknesses, and as such will be more suited for different tasks. This chapter will give a very brief overview of some of the ML algorithms.

Artificial Neural Networks usually perform better with continuous features, and multi-dimensional feature sets. Large datasets are also typically necessary to achieve high preci-
These algorithms also perform well even when class boundaries are diagonal or non-linear. A drawback of these algorithms is their lack of transparency, or interpretability, and their relatively slow training and classification [53].

Decision trees, on the other hand, perform better with discrete features, are several orders of magnitude faster than neural networks and are very interpretable. However, decision trees are unable to classify diagonally separated classes [53].

K-nearest neighbour algorithms have faster training than other algorithms but very slow classification. They are also very sensitive to irrelevant features and have low interpretability [53].

Hidden Markov Models are interpretable but are not well-suited for many problems with high dimensionality [53].

Fuzzy Inference Systems have slow training and a lot of parameters that must be set. This acts as a double-edged sword, since it allows an experienced user to tailor the algorithm to their liking but is a very daunting task to an unexperienced user or can lead to inaccurate results. However, fuzzy are very interpretable and for this reason are very used in medical settings [53].

As a result, it is impossible to declare that one algorithm is better than all others, as they all have their qualities and defects. Therefore, it is up researchers to analyse a particular problem and decide which algorithm is best suited for solving it.
Chapter 5

Electromyography

This chapter will review some fundamentals of Electromyography (EMG) signal. While chapter 3 focuses on the applications and history of this technique, this chapter will discuss the more technical aspects of EMG signal characteristics, acquisition and processing.

5.1. Introduction to EMG

EMG is a technique commonly used to read the bioelectrical signals produced by skeletal muscles when contracting for a wide variety of applications. Most notably, EMG signal can be used in therapeutic settings, as shown in chapter 3. There are two types of EMG: intramuscular (IM-EMG) and surface EMG (sEMG) [68]. Surface EMG has the major benefits of being easy to use and non-invasive, but can only provide information about superficial muscles, and is very sensitive to cross-talk phenomena, meaning it can record signal from multiple muscles, rendering this technique not specific [69]. Intramuscular EMG, on the other hand, can capture signal from only one muscle and is less susceptible to noise, but is invasive and harder to use, making it unpractical for many clinical applications [69]. For this reason, sEMG is used in most clinical and therapeutic settings, such as myoelectric prosthesis control [70], and this dissertation will deal with sEMG. Unless stated otherwise, EMG will refer to sEMG in this dissertation.

5.2. Signal Description and Characteristics

A nerve and the muscle fibers it innervates are called a motor unit. Once an action potential reaches a muscle fiber, it propagates through the motor fiber and is termed the motor action potential, or MAP. A motor unit action potential (MUAP) is the sum of all MAPs in a motor unit. The electromyographic signal is the sum of all the MUAPs firing near the electrode. Since the MUAPs are not synchronized, this sum can have positive and negative voltage values, ranging from -5mV to 5mV [68], and frequencies mainly ranging from 50 to 150 Hz [19]. However, some applications may require the recording of higher bandwidths, in the 150-500 Hz range, to detect subtle changes such as fatigue in the muscle fibers [70].
5.3. Signal Acquisition and processing

Since the amplitude of the signal is so low, it is very sensitive to noise and the adequate signal processing practices must be put into place to improve signal-noise ratio and assure proper quality of the data [68]. The first step to acquiring good quality EMG signal is the correct placement and fixation of the electrodes. Surface Electromyography for the Non-Invasive Assessment of Muscles, or SENIAM, has a detailed guide containing correct electrode placement for 28 different muscles, and explaining techniques such as correct skin preparation to ensure good contact between the electrodes and the skin and minimize noise sources [71].

The next step is choosing an appropriate EMG sensor. Depending on the application, different bandwidths of the electromyographic signal will need to be recorded, meaning that an adequate sampling frequency must be chosen. If only the main 50-150 Hz bandwidth is of interest, a 500 Hz sampling frequency would be sufficient for signal acquisition, however, for studying higher bandwidths higher frequencies are necessary [19]. According to the Nyquist-Shannon sampling theorem, the sampling frequency must be, at least, twice as high as the highest frequency component of the studied signal [72]. For this reason, many studies use a sampling frequency of 1000 Hz [47], [49], [73] or higher [2] [19] [11] in many gait analysis applications.

After the signal is acquired, the signal processing stage begins. The first step of processing EMG signal is rectification, since only positive values are of use, so the negative values must either be discarded (Half-wave Rectification) or the absolute of the signal must be taken (Full-wave Rectification). Usually, full-wave rectification is used [68]. Afterwards, filtering techniques should be used to reduce unwanted noise and improve signal-noise ratio [68]. In literature, both High-Pass and Low-Pass filters are used, while notch filters are avoided to minimize distortion of the original signal [68].

High Pass filters are used to remove low-frequency noise (baseline drift), which can be caused by several reasons, but mainly is due to motion artefacts (sliding of the muscle relative to the electrode), skin-electrode interface artefacts (thermal and electro-chemical noise) and the inherent instability of the signal due to the randomness in the firing rate of the motor units [68], [74]. There is no consensus as to what cut-off frequency or slope should be used for the High-Pass Filter, but many researchers follow the SENIAM guidelines, which use a 20 Hz, 12dB/oct Butterworth filter [49]. The Butterworth style filter is used because it has no ripples in the bandpass region, so the original signal is not distorted [74].

The Low Pass filter, which is designed to remove high frequency noise is typically used at the 400-500 Hz range because in this zone the amplitude of the noise usually surpasses the amplitude of the EMG signal [74].

Even when taking all the correct measures during signal acquisition and processing, it is near impossible to obtain a completely noise-free signal. Some sources of noise simply cannot be completely eliminated by standard methods [74], and so researchers must take extra care to check for their presence on the acquired signal. Two of these sources of noise are electrical background noise and baseline contamination with muscle activity. One way of correctly identifying these artefacts is to analyse the frequency spectrum of the signal, since electrical noise shows a big power spike at 50 Hz [75], and muscle activity contamination will show a frequency spectrum similar to muscle contraction but appears during periods when the patient is at rest. After the electromyoographic signal has been acquired, filtered and checked
for noise artefacts, researchers can begin studying the signal and retrieving information from it.

5.4. Feature Retrieval

Raw EMG is not a suitable candidate for determining gait periods or detecting gait events, due to its pseudo-random nature. As a result, researchers usually decompose the signal into several features [2], [34], [49], [39]:

- Raw EMG (r-RMG).
- Standard Deviation (SD).
- Root Mean Square (RMS).
- Mean Absolute Value (MAV).
- Integrated EMG (i-EMG).
- Waveform Length (WL).
- Zero Crossing (ZC).
- Slope Sign Changes (SSC).
- EMG Histogram (HIST).
- EMG Derivative (d-EMG).
- EMG Envelope (e-EMG).
- Autoregressive coefficients (AR).
- Mean Power (MNP)
- Peak Frequency (PKF)

This process is commonly mislabelled in literature as “Feature Extraction”. However, feature extraction is a dimensionality reduction process, where a signal or feature set is reduced to a more workable format, with minimal loss of relevant information (see chapter 4.3). Decomposing the EMG signal into SD, RMS, MAV and other features results in a lot of lost valuable information and increases dimensionality. Therefore, in this work we will label this process as “Feature Retrieval” to avoid any confusion with feature extraction.

Features can be retrieved from the time domain (TD); like RMS, MAV or SD; or from the frequency domain (FD); such as MNP or PKF. However, retrieving features from the FD is slower, since it requires signal transformation, and FD features often have reduced classification power, which makes them unsuited for real-time classification problems [67] [49]. The combination of retrieved features is called the original feature set, which will, by processes of feature selection and/or extraction, originate the feature set which will ultimately be fed to the ML algorithm for training and classification.
Chapter 6

Conclusion

This chapter will provide a brief summary of this report, mentioning the approached topics and the main conclusions that can be taken from this work. The “Future Work” section, presents the necessary steps to develop the ML algorithm and a Gantt diagram showing the expected workflow of the project.

6.1. Final Conclusions

The aim of this report is to cement the potential of using EMG signal to perform real-time gait partitioning for applications such as FES and MPC and develop a new machine learning algorithm to tackle this matter.

Gait partitioning is a gait analysis technique used to study the gait cycle, so a brief overview of the gait cycle and gait analysis was presented in chapter two before the concept of gait partitioning was approached. In fact, chapter two approached the following topics:

- The gait cycle, gait events and gait periods.
- The differences between kinematic, kinetic and muscle activity approaches to GA.
- The advantages and disadvantages of wearable sensors in gait analysis.
- The fundamentals and applications of gait partitioning.
- The final conclusion of chapter two chapter is that wearable sensors can be crucial for many GP applications like FES and MPC.

As a result, chapter three provides examples of different wearable systems used to perform GP, such as footswitches, IMUs and EMG sensors. It was reported in this chapter that EMG sensors are very versatile and therefore have great potential to be used for GP, despite requiring the use of complex machine learning algorithms to detect gait events from EMG signal. Another disadvantage of EMG sensors is their relatively low accuracy, which limits their use in real-life applications.

Chapter four focuses on machine learning. It describes the fundamental concepts of machine learning, such as feature selection and extraction, overfitting and algorithm evaluation. The final part of this chapter presents some of the strengths and weaknesses of ML algorithms commonly used to perform GP with EMG data.
Finally, chapter five discusses the basics of EMG, such as what is electromyographic signal, how it is acquired and processed, and what features can be retrieved from this signal to be use fed to the ML algorithm.

In conclusion, this report establishes the importance of EMG sensors for GP applications, and the problems associated with it. The goal of the report is to develop a robust machine learning algorithm that can be used for real-time GP with satisfactory accuracy, using EMG sensor data. Fundamental concepts of EMG, machine learning, gait analysis and the gait cycle are described, since they are essential components of this issue.

6.2. Future work

This report laid the theoretical foundations for the creation of a robust, EMG-based, ML algorithms that can perform real-time GP. However, there are several steps that must be taken before such an algorithm becomes a reality.

The first step is data acquisition and labelling. The EMG data must be synchronously acquired with a reference system, such as VICON or force plates in order to be labelled. Labelling data involves performing gait event detection with the reference system. These labels will later be used to compare the reference system and the EMG algorithm classification. It is important to acquire enough data to allow the algorithm to train efficiently, so enough trials should be performed to allow for accurate classification. At an early stage, this acquisition should be performed in controlled conditions, with normal gait subjects.

The second step is the processing of EMG information, which is described in section 5.3. This involves selecting the relevant frequencies to the problem, the type of filters used and the features that should be retrieved and used in the original feature set.

The third step covers the implementation of the machine learning algorithm, which will occupy the bulk of the time invested in this dissertation. First, a suitable machine learning algorithm must be chosen, taking into account their advantages and disadvantages. If an algorithm such as FIS, which has many adjustable parameters, a combination of parameters must be found that yields good accuracy without being too computationally heavy. Appropriate feature selection and feature extraction methods must be selected, based on the algorithm choice and the original feature set, and used to obtain the optimal feature subset. In addition, an algorithm evaluation method, such as k-fold cross validation must be chosen, as well as the evaluation criterion used to estimate the algorithm's performance. In this scenario, an appropriate selection criterion is the average time delay between the classifier's and reference system's detection of a gait event, since this is the main metric that will dictate the suitability of the algorithm to perform real-time GP.

After a suitable algorithm, parameters, feature subset, evaluation method and stopping criterion have been chosen, the training and validation phases can begin. In the training phase, the classifier will use the training set data to form its classification model, and in the validation phase, it will validate its model on the validation data set. At the end of this process, the algorithm will provide an estimate for its performance, called the evaluation criterion. If deemed necessary, different algorithms, parameters, feature subsets and stopping criterions can be used, to evaluate their effect on the classifier's performance.

When the classifier's performance meets the proposed requirements, different variables can be introduced into the system. A new dataset, containing pathological gait or sloped sur-
face gait can be created and fed to the algorithm to check if the algorithm is robust to these factors.

If all steps work according to plan, the final step would be to use the algorithm to control in real-time an actual motorised prosthesis and check if any problems emerge from the real-life application.

The Gantt diagram of the dissertation is presented below. This diagram is divided into 6 tasks:

- Task 1: Literature study.
- Task 2: Data acquisition and labelling.
- Task 3: Signal processing.
- Task 4: Development of ML algorithm.
- Task 5: Testing of algorithm’s robustness.
- Task 6: Real-world testing of algorithm’s robustness (optional).
- Task 7: Writing the dissertation.

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Figure 6.1 - Gantt diagram of the dissertation work.
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