Universidade do Minho
Escola de Engenharia
Departamento de Eletrónica

Marta Sofia Guimarães Cardoso

High-Tech Aid Tool To Monitor Postural Stability In Parkinson's Disease

Master Dissertation
Integrated Master's in Biomedical Engineering

Project supervised by
Cristina Manuela Peixoto Santos

December 2022

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity.

I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

ABSTRACT

Parkinson's disease (PD) is a neurodegenerative disease that affects around 1% of the population over 65 and has increased in prevalence in recent years. One of the most disabling motor symptoms and a major contributor to falls is postural instability, which threatens the independence and well-being of people with PD. Usually, physicians assess this symptom with a traditional clinical examination named pull test, which, although easy to administer without requiring any instruments, it is a difficult test to standardize and lacks sensitivity to small but significant changes. Thus, other approaches based on high technologies have emerged to provide objective metrics and long-term data on postural stability, complementing clinical assessment. Wearable sensors appeared as a promising tech-based solution to better capture postural instability and eliminate the subjectivity of postural-associated clinical examinations.

This dissertation proposes the design, development and validation of a postural assessment tool to perform more objective evaluations of postural instability during basic dynamic day-to-day activities. To achieve this goal, the following steps were accomplished: (i) create a dataset based on 3D motion data of PD patients performing the pull test and dynamic activities using an inertial measurement unit (IMU); (ii) extract relevant features from the data collected, conduct an extensive statistical search, and find correlations to clinical scales; (iii) implement a tool based in artificial intelligence (AI) to classify the level of postural instability through the data collected. Different deep learning models were designed and several combinations of data input were considered in order to find the best model to predict the pull test score.

Overall, satisfactory results were achieved as the statistical analysis revealed that many features were considered relevant to distinguish between the scores of the pull test, for diagnostic purposes and also to differentiate the several stages of the disease and levels of motor disability.

Regarding the AI-based tool, the results suggest that the combination of IMU-based data with deep learning may be a promising solution for postural instability assessment. The model that achieved the best performance in the testing phase with unseen data presented an accuracy, precision, recall and F1-score of approximately 0.86. The results also show that when fewer daily activities are included in the dataset,

the complexity of the model reduces, making it more efficient. Despite the promising results, more data should be collected to assess the actual performance of the model as a postural assessment tool.

Keywords Artificial Intelligence, Inertial Measurement Unit, Parkinson's Disease, Postural Instability, Pull Test Score

RESUMO

A doença de Parkinson (DP) é uma doença neurodegenerativa que afeta cerca de 1% da população acima de 65 anos e cuja prevalência tem aumentado nos últimos anos. Um dos sintomas motores mais incapacitantes e um dos principais contribuintes para quedas é a instabilidade postural, que ameaça a independência e o bem-estar das pessoas com a DP. Normalmente, o teste utilizado para avaliar a instabilidade postural é o *pull test*, que, embora fácil de executar e não necessitando de qualquer instrumento, é um teste difícil de padronizar e com falta de sensibilidade para detetar pequenas alterações que podem ser significativas. Assim, os sensores vestíveis surgiram como uma solução promissora para capturar a instabilidade postural e eliminar a subjetividade dos exames clínicos associados à postura.

Esta dissertação tem como objetivo o idealizar, desenvolver e validar um instrumento para realizar avaliações mais objetivas da instabilidade postural durante atividades dinâmicas básicas do dia-a-dia. Para atingir esse objetivo, as seguintes etapas foram realizadas: (i) criar um *dataset* baseado em dados de movimento 3D de pacientes com a DP equanto executam o *pull test* e atividades dinâmicas através de uma unidade de medida inercial; (ii) extrair características relevantes dos dados adquiridos, realizar uma extensa pesquisa estatística e encontrar correlações com escalas clínicas; (iii) implementar uma ferramenta baseada em inteligência artificial (IA) para classificar o nível de instabilidade postural através dos dados recolhidos. É de notar que diferentes frameworks de *deep learning* foram projetados e vários *datasets* foram considerados de modo a encontrar o melhor modelo para prever a pontuação da escala do *pull test*.

No geral, os resultados alcançados foram satisfatórios, pois o estudo estatístico revelou que muitas das características extraidas dos sinais recolhidos foram consideradas relevantes para distinguir entre as pontuações do *pull test*, para fins diagnósticos e também para diferenciar os estágios da doença e os níveis de incapacidade motora.

Em relação à ferramenta baseada em IA, os resultados apresentados sugerem que o *deep learning* pode ser promissor na área de avaliação de instabilidade postural através de IMUs. O modelo que obteve o melhor desempenho apresentou uma exatidão, precisão, sensibilidade e *F1-score* no teste de aproximadamente

0.86. Os resultados também mostram que *dataset* com um menor número de actividades diferentes incluídas leva a que o modelo se torne menos complexo, tornando-o mais eficiente. Apesar dos resultados promissores, mais dados devem ser recolhidos para avaliar o real desempenho do modelo como ferramenta de avaliação postural.

Palavras-chave Doença de Parkinson, Escala do *Pull test*, Inteligência Artificial, Instabilidade Postural, Unidade de Medição Inercial

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LIST OF ACRONYMS

2CABraga	Clinical Academic Centre of Braga
ABC	Activity-specific Balance Confidence
Acc	Accelerometer
AI	Artificial Intelligence
AP	Anterior-Posterior
AS	Asymmetry
AUC	Area Under Curve
BiRD LAB	Biomedical & Bioinspired Robotic Devices Laboratory
BBS	Berg Balance Scale
CF	Centroidal Frequency
CMEMs	Center of MicroElectroMechanical Systems
CNN	Convolutional Neural Networks
CoM	Center of Mass
CoP	Center of Pressure
DHI	Dizziness Handicap Inventory
FC	Final Contact
FN	False Negative
FP	False Positive
FR	Functional Reach

Gyr	Gyroscopes
HC	Healthy Controls
HRPD	High Risk for Parkinson's Disease
HW	Hardware
H&Y	Hoehn and Yahr
IC	Initial Contact
IMU	Inertial Measurement Unit
LOS	Limits of Stability
LSTM	Long Short-Term Memory
ML	Medial-Lateral
MLP	Multilayer Perceptron Networks
MV	Mean Velocity
PD	Parkinson's Disease
PIGD	Postural Instability and Gait Difficulty
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ReLUs	Rectified Linear Units
RMS	Root Mean Square
ROC	Receiver Operating Characteristics
RoM	Range of Motion
RQ	Research Questions
SBDT	Standard Balance Deficit Test
SD	Standard Deviation
SOT	Sensory Organization Test
SW	Software

TUG Timed Up and Go

UPDRS Unified Parkinson's Disease Rating Scale

VT Vertical

WDPA Wearable Devices for Postural Assessment

1

INTRODUCTION

This dissertation, entitled "High-tech aid tool to monitor postural stability in Parkinson's disease", presents the work developed throughout the academic year of 2021-2022 in the scope of the fifth year of the Integrated Master's in Biomedical Engineering, at University of Minho. The research was developed in the Biomedical & Bioinspired Robotic Devices Laboratory (BiRD LAB) at the Center for MicroElectroMechanical Systems (CMEMs) established in University of Minho, Braga, Portugal. Moreover, the experimental trials with pathological end-users were carried out in Hospital of Braga with the collaboration of the physicians from Clinical Academic Centre of Braga (2CABraga).

1.1 Motivation, Context and Problem Statement

After Alzheimer's, Parkinson's disease (PD) is the most common neurodegenerative disease worldwide, affecting around 1% of the population over 65, and its increase in prevalence has been documented in the past decades [1, 2]. PD cardinal features consist of tremor at rest, rigidity, akinesia (absence of movement) or bradykinesia (slowness of movement) and postural instability, although it is important to point out that the symptoms and the rate of progression of this disease differ between individuals [3, 4].

Parkinson's is a disease that affects more men than women and usually appears after the age of 60. This disease is caused by the impairment or death of the nerve cells in the basal ganglia, which is an area in the brain that controls movement, leading to a decrease in dopamine production and, consequently, to movement problems. On the other hand, the non-movement symptoms in PD can be explained by the loss of nerve endings that produce norepinephrine [4].

Currently, **there are no medical tests to accurately detect this disease**. PD diagnosis is mainly based on medical history and a neurological examination. Many times, early Parkinson's symptoms are mistaken for the typical effects of aging, as they are subtle and occur gradually. Furthermore, **there is still no cure** for PD, although there are specific treatments that can relieve part of the symptoms [4].

The stage of the disease in Parkinson's is estimated through rating scales. These tools are very useful for physicians and researchers since they allow gathering information about the course of the disease and help to evaluate and manage treatment strategies. The **rating scales most commonly used are the Unified Parkinson's Disease Rating Scale (UPDRS) and Hoehn and Yahr (H&Y) scale** but, usually, more than one rating scale is used to perform the appraisal in order to get a wider perspective of the symptoms [5].

The UPDRS is a scale that comprises four sections: I - Non-Motor Aspects of Experiences of Daily Living (13 items); II - Motor Aspects of Experiences of Daily Living (13 items); III - Motor Examination (33 items); IV - Motor Complications (6 items). Each item is assigned a score from 0 (normal) to 4 (severe problems) and the total score can go up to 260. The higher the score, the greater the degree of disability. The H&Y scale divides this pathological condition into seven stages according to the level of disability, as shown in Figure 1. This is a quick and practical tool that distinguishes a mild-to-moderate stage of the disease (H&Y 1 to 3) from a severe stage (H&Y 4 and 5) [5].

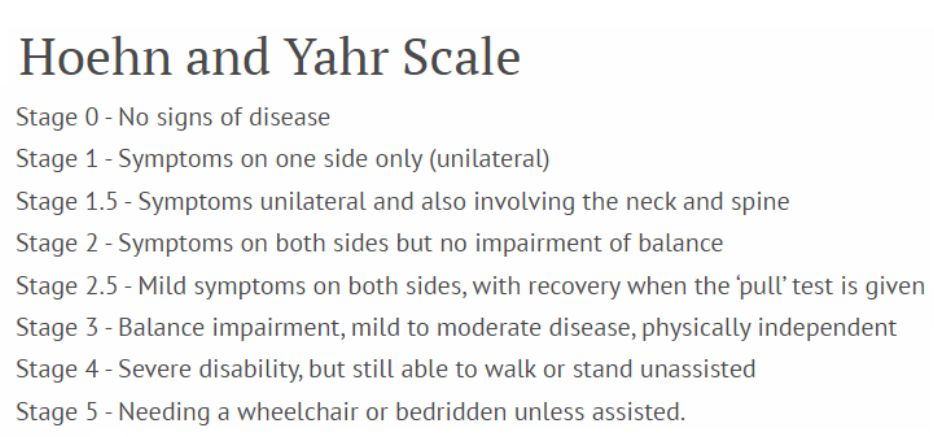

Figure 1: Modified Hoehn and Yahr scale [5].

It is very common for people with PD to go through gait and postural complications, such as freezing, dysrhythmic and slow gait, flexed posture and decreased postural responses. In fact, **postural instability**

is one of the most disabling motor symptoms and a major contributor to falls, and as a result, it threatens the independence and well-being of people with PD, diminishing their quality of life. Usually, this feature is only discernible later in the course of the disease. Despite that, it can be present at diagnosis and, as the disease progresses, becomes more prominent [2, 3, 6].

In order to monitor patients over time and implement an adequate treatment to improve postural stability and reduce the risk of falls, it is important for physicians to quantify gait and balance deficits and to perceive motor changes that lead to postural complications. Generally, the clinical examination used to assess postural instability is a test denominated by **pull test**, also known as the **retropulsion test**, which corresponds to item 12 of the motor section of the UPDRS (Part III). *"The test examines the response to sudden body displacement produced by a quick, forceful pull on the shoulders while the patient is standing erect with eyes open and feet comfortably apart and parallel to each other"* [7]. To perform the test, the examiner pulls the patient backwards by the shoulders with enough strength to displace the center of gravity and make the patient take a step back. After that, the examiner grades the corrective postural response, based on the number of steps or fall, using a five-point scale (0-4), as shown in Figure 2 [2, 6].

3.12 POSTURAL STABILITY

0: Normal:	No problems. Recovers with one or two steps.
1: Slight:	3-5 steps, but subject recovers unaided.
2: Mild:	More than 5 steps, but subject recovers unaided.
3: Moderate:	Stands safely, but with absence of postural response; falls if not caught by examiner.
4: Severe:	Very unstable, tends to lose balance spontaneously or with just a gentle pull on the shoulders.

Figure 2: Pull Test - Item 12 of the motor section of the UPDRS [7].

The direction of the perturbation used to perform the pull test is considered one of the most destabilizing. Nevertheless, healthy subjects are able to regain their balance with two or even one large step, with the help of the hip and the arms to counterweight. In contrast, PD patients with balance impairment are forced to take more steps, considering their steps to correct balance are often rapid and shorter and that they have reduced arm swing due to the increased muscle rigidity [2, 8].

The **pull test** is widely used since it is **easy to administer, does not require specific instruments and marks a transition in the H&Y scale to stage 3**, allowing to distinguish between a milder stage of PD (H&Y 1 and 2) and a moderate or severe stage (H&Y 3 to 5). In spite of that, it presents several limitations which prevent physicians from accurately monitoring the progression of the disease. In fact, it is **difficult to standardize this test** considering: (i) the variability of the pull force applied, existing an inherent subjectivity to interpret and score the examination; (ii) has a very limited scaling; (iii) it lacks sensitivity to detect small but significant changes in balance and, consequently, the patients that are at a higher risk of falling; (iv) has poor reliability and is limited by physician's bias [6, 9, 10].

In addition, the pull test **cannot distinguish between healthy subjects and PD patients in which the impairment of postural responses is not evident**, considering these patients are typically able to regain balance within two steps. In fact, several studies have shown that, in early stages of Parkinson's, patients already exhibit decreased postural responses and can be destabilized more easily than healthy subjects due to inefficient postural adjustments [2, 11].

To overcome the pull test as a standard examination of patients' postural instability, instrumented analysis has been proposed with the use of force platforms and motion capture technologies. The force platform is a technology that allows the measurement of the center of pressure (CoP), defined as the location of the resultant vertical force on the force platform surface. Through the displacement of this measure, it is possible to obtain postural movements made by an individual while trying to maintain a balanced position. Motion capture technologies, such as Microsoft Kinect or MOCAP, use cameras (and other devices) to identify the position of the joints in order to perform an analysis. Both pieces of equipment increase the objectivity of the evaluation of postural instability and place minimum constraints on the subject. However, they have a limited clinical adoption because they are expensive, require a lot of space and time to set up and lack portability [12, 13].

Wearable sensors emerged as promising solutions to **better capture postural instability and eliminate the subjectivity of postural-associated clinical examinations**. Despite being frequently used in motion assessment research and showing promising results, it is required to gather more scientific knowledge and further exploration about wearable sensors' application in clinical settings to monitor the postural stability of patients with PD. In fact, wearable sensors **have not yet been adopted in hospitals or clinical institutions as a standardized tool to complement clinical examinations**. A possible

reason includes the lack of consensus in terms of sensor configurations (number and placement), but above all, about the correct protocol and measures to be considered in postural assessment [9, 14, 15].

Furthermore, **wearable technology can be used in the context of rehabilitation and assistance to provide biofeedback**. Indeed, biofeedback devices emerged as a front-end solution to mitigate parkinsonian gait-associated disabilities. These systems make use of wearable sensors that enable sensory acquisition and trigger cue information (biofeedback). Through meaningful sensory cues, patients can improve and become aware of their balance disorders which could lead to a change in their postural control. The biofeedback cues can be provided through various means, including visual, auditory and/or vibrotactile cueing and supply information on how to perform or the outcome of a movement. The use of sensory cues is a well-established technique for treatment of these kinds of impairments and its positive effects have been verified in multiple studies. Additionally, it can be used to make an event happen with more frequency (positive reinforcement) or less frequently (negative reinforcement) [15].

Taking all this into consideration, it becomes crucial to study the ability of a robust wearable system combined with AI algorithms to assess postural instability in PD patients (so a more objective evaluation can be carried out) and to provide additional sensory information (in order to enhance these patients' motor performance).

1.2 Goals and Research Questions

The main goal of this dissertation is the **design, development and validation of a postural assessment tool** to make a more objective evaluation of postural instability under dynamic conditions.

Considering this main goal the following objectives were established:

Goal 1: Identification and analysis of the current state-of-the-art of postural-related works in PD aiming to critically specify their achievements and limitations to take a systematic approach to address on this dissertation. Chapter 2 presents these surveys.

Goal 2: Create an open-source multimodal dataset of the pull test and physical activities in PD based on 3D motion data and kinematic-driven gait parameters acquisitions through wearable miniaturized inertial sensors. The details for the data acquisition are stated in chapter 3.

Goal 3: Extraction of gait and postural-related features from the data acquired and conduction of an extensive statistical research to determine if and which features are considered significant to distinguish between the different levels of postural instability. Furthermore, accomplishment of clinical correlations to contribute to a clinical diagnostic tool. This goal is addressed in chapter 4.

Goal 4: Implementation of a new PD-oriented tool to assess dynamical postural instability. It is projected the design and development of a new AI-based tool capable of assessing patients' posture instability through raw inertial data acquired during the execution of dynamic tasks. This goal is addressed in chapters 3 and 5.

In order to achieve the main goal of this dissertation, the following research questions were identified:

RQ1: How is postural instability usually assessed?

RQ2: Is there a more objective way to assess postural instability?

RQ3: Can metrics extracted from inertial data of daily activities be correlated to the pull test score? And to the UPDRS-III score, the H&Y score or for diagnosis purposes?

RQ4: Can deep learning be used to classify the pull test score through inertial data of daily activities to increase the objectivity of postural instability assessment?

1.3 Contribution to Knowledge

The main contributions of this dissertation to knowledge are:

- A review of the use of wearable technology to assess postural responses and provide additional sensory information in order to improve postural control;
- An open-source multimodal dataset based on 3D motion data of PD patients performing the pull test and dynamic activities using an inertial measurement unit (IMU) on the CoM;
- An extensive statistical search to determine if the gait and postural-related features extracted from the inertial data of dynamic activities are considered significant to distinguish between the different levels of postural instability and of motor disability, the different stages of the disease and for diagnostic purposes;
- A deep learning solution to assess postural instability by predicting the pull test score through inertial data of dynamic activities.

The work developed led to the elaboration of a journal paper entitled "Objective Assessment of Postural Instability in Parkinson's Disease under Dynamic Conditions" (under revision).

1.4 Dissertation Outline

This dissertation is organized into 6 chapters, as follows.

Chapter 2 presents the state-of-the-art regarding the use of wearable technology to evaluate postural responses and provide additional sensory information in order to improve postural control.

Chapter 3 provides an overview of the components and methods used in this dissertation to acquire and process the data. Additionally, it describes the features of the APP developed in Python to load and process the inertial data acquired during dynamic tasks in order to estimate gait and postural-related metrics and to predict the pull test score through an AI-based algorithm.

Chapter 4 comprises a description of the features extracted from the inertial data collected during the execution of the dynamic tasks and how these are expected to behave with the pull test score. This is followed by a brief explanation of the statistical analysis that was performed using SPSS, the results and subsequent analysis of the findings.

Chapter 5 provides a description of the three deep learning frameworks employed with the purpose of predicting the pull test score through inertial data acquired during the execution of the dynamic tasks or through features extracted from the data. Therefore, the chapter starts by summarizing how the datasets are prepared and the training pipeline, followed by the results, discussion and conclusions taken from the AI-based algorithms created.

Chapter 6 addresses the main conclusions of this dissertation and provides topics for future work.

2

STATE OF THE ART

In this chapter is presented a brief literature review regarding existing devices to assess postural instability in PD to various aims. To that end, the chapter begins with a concise introduction to postural instability in PD and the main issues of the current rehabilitation programs to enhance motor performance. This is followed by an analysis of the devices in terms of their technological components (type and configuration), their protocol to acquire data and evaluate patients' progress, and the validation methodologies of the studies.

2.1 Introdution

Postural stability or balance can be described as the ability to keep the body's center of mass (CoM) within limits of stability (LOS), through static and dynamic conditions. Indeed, postural stability is **crucial to autonomously accomplish basic daily tasks** such as walking or even standing, and it can be achieved by the interaction of the visual, vestibular and somatosensory systems [16].

Postural instability and gait disabilities are amongst the most incapacitating features of PD and threaten the independence and quality of life of PD patients. In fact, postural instability can be characterized by a decrease of the LOS, the magnitude of postural responses and postural reflexes, which affect the performance of both static and dynamic activities. In order to monitor patients' postural conditions and implement an adequate treatment to improve postural stability, it is crucial for physicians to quantify gait and balance deficits and to perceive changes that lead to postural complications [2, 6]. Physicians benefit from continuous and objective data about the state of patients' postural stability. To overcome the subjectivity of the current clinical examinations, as the pull test, tech-based assessment has been proposed by using wearable technology [17–20]. Indeed, wearable sensors have proven to be a promising solution to be used in

different settings, like during consultations, but also in patients' homes. Besides, these solutions are easily accepted by patients given their low weight and size, and are able to acquire data that can be applied to empirical mathematical calculations or more intelligent algorithms to estimate relevant postural metrics.

Currently, **there is no consensus regarding meaningful metrics to quantify postural instability**. Several articles have studied the assessment of postural control during quiet stance by extracting sway measures and concluded that these metrics are relevant to characterise balance and identify individuals with balance impairments [9, 12, 16, 21]. However, gait can also provide valuable parameters to assess postural stability [17–19, 22]. Nevertheless, it is not clear which wearable miniaturized sensors could be applied and which should be their body location to provide these metrics information. Besides, **there is no explicit evidence about which protocols and clinical examinations should be accomplished to obtain more objective data**. Furthermore, there is a need to clarify the posture-related state-of-the-art in the PD field, if the motor metrics used to assess postural instability have been applied on biofeedback devices to provide additional sensory information during rehabilitation programs [22, 23].

Surgical and pharmacological treatments are not effective in improving impairments in balance with the disease progression, and it was even stated that some treatments cause further deterioration in postural control, leading to an increased risk of falls and limited motor performance [24, 25]. For that reason, motor rehabilitation programs are an essential complement to these typical treatments. However, patients often do participate in balance training programs due to the expenses, lack of motivation or availability of physical therapists or because it is required to move to a dedicated rehabilitation space. Even if some exercises are given to perform at home, patients' willingness tends to be lower when there is no real-time feedback about their performance during training sessions. Thus, **the use of biofeedback during rehabilitation training has been shown to improve task learning and retention**. Therefore, there is an interest in developing devices capable of augmenting compromised sensory information by providing meaningful cues (biofeedback) [2, 16, 26, 27].

In order to provide feedback about patients' postural behaviour with the main goal of helping them to accomplish correct postural adjustments, it is necessary to extract suitable posture-related measures. Wearable miniaturized sensors appeared to provide these outcomes, being easily integrated into patients' day-to-day activities without interfering with their movements [27, 28].

In light of the need to better understand the state-of-the-art over the past 12 years, this comprehensive review critically analyses the scientific contributions of wearable devices for postural assessment (WDPA) in PD to capture and evaluate posture & balance-related parameters and provide additional sensory cues to improve overall stability in individuals with PD. Beyond that, an overview of these devices will be presented concerning their sensor/actuator type and configuration, their protocol to acquire data and evaluate patients' progress, and the validation methodologies of the studies. Therefore, it is expected this review to answer the following research questions (RQ): (RQ1) "How have the WDPA been applied in PD?"; (RQ2) "Which technologies were integrated in the WDPA, what are their settings parameters and where were they placed within the body?"; and (RQ3) "How have the WDPA been clinically validated in PD?".

2.2 Search Strategy and Eligibility Criteria

A literature search was conducted on three electronic databases (Google Scholar, PubMed and Web of Science) to identify articles that describe an objective way to assess postural instability in people with PD, using wearable sensors, and/or a biofeedback strategy to enhance postural control. Additionally, the reference list of some of the articles identified was searched to find even more relevant studies on the subject. The survey was performed following the guidelines of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), as represented in Figure 3. For that purpose, the keywords used to carry out the literature search were: ["Parkinson's Disease AND Postural Instability AND Wearables"]; ["Postural Instability AND Sensitive Measures AND Instrumented Test"]; ["Pull Test Estimation AND Wearable Sensors"]; ["Biofeedback System AND Postural Control AND Parkinson's Disease"]; and ["Postural Stability AND Biofeedback AND Parkinson's Disease"].

The inclusion criteria the studies had to fulfill to be comprised were: (i) be validated with idiopathic PD; (ii) integrate wearable technology; (iii) have applicability to assess postural stability and/or improve postural control through the use of biofeedback systems as part of rehabilitation or assistance strategies; and (iv) be published in the English language and within the past 12 years.

2.3 Results

2.3.1 General results

Through the literature search, a total of 123 articles were identified as being potentially eligible for the review. After removing the duplicates, the articles were screened by title and by abstract, in that order, to exclude the ones that were not within the correct topic, leaving a total of 36 papers. The remainder of the studies were thoroughly analysed to assess the ones that met the inclusion criteria and to exclude those that veered off from the theme and the less appropriate ones. Overall, 17 articles were included in the review. This approach is represented in more detail in Figure 3.

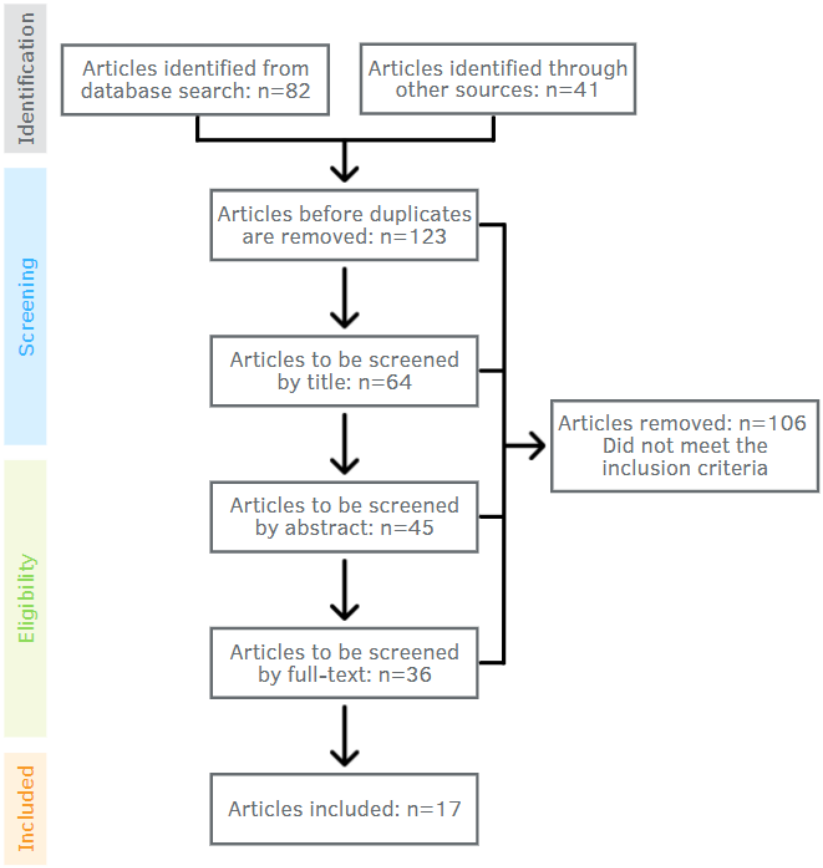

Figure 3: Flowchart for the search strategy based on PRISMA.

The selected articles were divided into categories regarding the aim of their study (diagnosis, disease severity/progression, rehabilitation). Furthermore, these were analysed in terms of the technological components included in their devices (type, number, location within the body and sampling or vibration frequency of the sensors and actuators used, when applicable), and their validation methodologies.

2.3.2 Studies purpose: postural instability in PD

After reading and analysing the selected articles, these were divided into three categories according to their underlying goal. All of the articles shared a common purpose, which was to characterize postural stability or related parameters through the means of wearable sensors. Despite that, the metrics identified were used for the following:

1) **Diagnosis** – studies that used the data collected to distinguish PD patients from healthy controls (HC).
2) **Disease severity/progression** – articles that seek to find a correlation between the data and clinical scales used to establish the severity of the disease or perceive how the disease is evolving over time in a patient.
3) **Rehabilitation** – articles that explore the use of biofeedback to improve postural control in PD patients.

Table 1 presents the goal, strategy and main contribution of all articles selected.

Table 1: Main goal and description of the articles that study postural instability and related parameters.

Ref	Goal	Description
[17]	Diagnosis	Identify mobility deficits in subjects in early stages of PD and with no apparent impairments in motor performance.
[18]	Disease severity	Find a correlation between gait and turning parameters and disease severity.
[9]	Disease severity	Find a correlation between sway measures and clinical scales.
[16]	Diagnosis	Distinguish PD patients in early stages of the disease with no signs of balance problems through sway measures.
[28]	Diagnosis	Separate HRPD from PD patients and from HC with the FR distance and sway metrics.
[19]	Diagnosis	Differentiate PD by examining peak accelerations from gait.
[20]	Diagnosis	Detect PD by evaluating back rigidity.
[12]	Diagnosis	Distinguish PD patients by analysing sway metrics using a mobile device.
[21]	Disease progression	Study of the disease progression over a year by analysing changes in postural sway.
[22]	Diagnosis	Discriminate PD patients through gait metrics.
[29]	Rehabilitation	Improve posture, static and dynamic balance and activities of daily living (and retain) with audio biofeedback.

Continued on next page

Table 1 – *Continued from previous page*

Ref	Goal	Description
[30]	Rehabilitation	Improve balance by providing biofeedback through vibrotactile cues.
[24]	Rehabilitation	Improve overall stability (and retain) with vibrotactile biofeedback.
[25]	Rehabilitation	Discover which type of cue is better to improve dynamic balance.
[26]	Rehabilitation	Find which coding scheme works better to improve dynamic balance.
[31]	Rehabilitation	Improve gait performance (and retain) with cued training.
[27]	Rehabilitation	Improve balance and gait with multimodal biofeedback training.

HRPD - High Risk for Parkinson's Disease; **FR** - Functional Reach

2.3.3 Technologies integrated into postural assessment devices in PD

Table 2 depicts some features of the WDPA developed in the past twelve years that quantify postural responses so that it is possible to make more objective evaluations or even to provide a more effective motor rehabilitation through biofeedback. All devices included a sensory system responsible for recording body movement. Additionally, some WDPA also include an actuation system, that provides sensory information through external cues. For each system, the technologies were analysed regarding the type of sensor or actuator and, when applicable, their settings, quantity, and location within the body.

Regarding the sensory system, all the devices integrated inertial measurement units (IMUs) [12, 17–21, 25–27], accelerometers (Acc) [9, 16, 22, 28, 29, 31] and/or gyroscopes (Gyr) [24, 29, 30]. These sensors were placed in forearms/wrist [17, 18], shanks [17, 18, 27, 31], thighs [17], feet [19], sternum [17, 18, 27, 31], 4 corners of the back [20], but mostly in the lower back, near the body's center of mass [9, 12, 16, 21, 22, 24–30]. With exception of five of the seventeen studies, that used between four and seven sensors [17, 18, 20, 27, 31], the majority of the devices comprehend only one [9, 12, 21, 22, 25, 26, 28] or two [16, 19, 30] sensors. Lastly, the sampling frequency varied between 25 and 200 Hz, although most studies used either a frequency of 50 [9, 16, 21, 22, 27] or 100 Hz [12, 19, 25, 26, 28] for data acquisition. However, four studies did not provide this information [20, 24, 29, 30].

Concerning the actuation system, only the studies which aim rehabilitation integrated this kind of setup. These systems provided information about body motion through auditory [27, 29, 31], visual [25, 27, 31], vibrotactile [24–26, 30, 31] or even a mix of these types of cues [25, 27]. The devices that used vibrotactile biofeedback incorporated between 1 and 8 vibrating actuators (motor tactors), depending on the body

location. The preferred configuration for the tactors was 4 around the waist (front, back, and right and left) [24–26], near the body's center of mass, even though there was a study that placed a tactor in the wrist [31] and another that used 8 around the head [30]. The vibration frequency of the tactors was either fixed at 250 Hz [25, 30] or varied between 150 to 250 Hz [26] as these values are within the human perception range, yet this information was omitted in two of the studies [24, 31].

Table 2 also contains information about the processing data methods adopted to prepare and treat the acquired data from the sensors to measure and estimate the postural metrics to be used on an evaluation or training/assistance goal. In regard to papers that aimed diagnosis or to study the disease severity/progression, the data processing was achieved through mathematical methods, in which several metrics were estimated by performing empirical calculations [9, 12, 16–22, 28, 31]. The remainder of the studies used threshold [25–27, 30] or range-based methods [24, 26, 29] to provide biofeedback. The threshold-based methods consisted in defining a threshold value that, when exceeded, a signal was emitted. The range-based methods are similar, but the signal emitted was modulated, the settings of the sensory cueing were controlled by a stratified threshold-range, i. e., in the case of vibrotactile biofeedback, the vibration frequency increased with the deviation of a certain parameter to the threshold value [26].

Table 2: WDPA developed for PD in the past twelve years.

Ref	Goal	Sensor Module				Actuation Module				Processing Data Methods
		Type	Num	Location	Freq	Type	Num	Location	Freq	
[17]	Diagnosis	IMU	7	Forearms, Shanks, Thighs and Sternum	200 Hz	-	-	-	-	Mathematical
[18]	Disease severity	IMU	5	Wrist, Shanks and Sternum	200 Hz	-	-	-	-	Mathematical
[9]	Disease severity	Acc	1	Lower Back (L5)	50 Hz	-	-	-	-	Mathematical
[16]	Diagnosis	Acc	2	Lower Back (L5)	50 Hz	-	-	-	-	Mathematical
[28]	Diagnosis	Acc	1	Lower back	100 Hz	-	-	-	-	Mathematical
[19]	Diagnosis	IMU	2	Feet (laterally below the ankle joint)	102.4 Hz	-	-	-	-	Mathematical
[20]	Diagnosis	IMU	4	4 corners of the back	-	-	-	-	-	Mathematical
[12]	Diagnosis	IMU	1	Lower Back (S2)	100 Hz	-	-	-	-	Mathematical
[21]	Disease progression	IMU	1	Lower Back (L5)	50 Hz	-	-	-	-	Mathematical
[22]	Diagnosis	Acc	1	Lower Back	50 Hz	-	-	-	-	Mathematical
[29]	Rehabilitation	Acc and Gyr	-	Lower back (L2-L5)	-	Auditory	-	-	-	Range-based models
[30]	Rehabilitation	Gyr	2	Lower back (L1-L3)	-	Vibrotactile	8	Head	250 Hz	Threshold-based models

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Table 2 – *Continued from previous page*

Ref	Goal	Sensor Module				Actuation Module				Processing Data Methods
		Type	Num	Location	Freq	Type	Num	Location	Freq	
[24]	Rehabilitation	Gyr	-	Lower Back (near the body's CoM)	-	Vibrotactile	4	Lower back (front, back, and right and left)	-	Range-based models
[25]	Rehabilitation	IMU	1	Lower Back (L5/S1)	100 Hz	Visual and/or Vibrotactile	4	Lower back (front, back, and right and left)	250 Hz	Threshold-based models
[26]	Rehabilitation	IMU	1	Lower Back (L5/S1)	100 Hz	Vibrotactile	4	Lower back (front, back, and right and left)	Variable (150-250 Hz)	Thresholds/Range-based models
[31]	Rehabilitation	Acc	5	Each leg and three placed on the lower third of the sternum	25 Hz	Auditory, Visual, Somatosensory or None	1	Wrist	-	Mathematical
[27]	Rehabilitation	IMU	6	Upper trunk, lower trunk and lower limbs	50 Hz	Visual and Auditory	-	-	-	Threshold-based models

2.3.4 Validation methodology highlights: participants, criteria study, metrics, and results

Tables 3 and 4 comprise relevant information about the validation methodology of the studies identified. In Table 3 is highlighted the number and type of participants included in the study, the evaluation of the participants with PD through rating scales and the inclusion and exclusion criteria used for the participants' selection. As for Table 4, it summarizes the experimental protocols, the metrics identified in the studies as being relevant, how the data analysis was performed and significant results.

All of the studies included a group of individuals with PD and the majority of them also had a healthy control group [9, 12, 16–22, 25, 26, 28] to compare the results. One study that aimed diagnosis even integrated subjects with high risk for Parkinson's disease (HRPD) [28].

The scales most commonly used to perform the appraisal of the severity of the disease of the participants with PD at baseline were UPDRS, UPDRS-III and H&Y. In addition, one study also included the Berg Balance Scale (BBS) [27] and two others incorporated subs-cores of UPDRS-III, such as Postural Instability and Gait Difficulty (PIGD), Bradykinesia and Rigidity sub-score [12, 21]. These scores and UPDRS-III help to get a better perspective of patients' motor function.

The criteria for the participants selection comprehends a diagnosis of PD, the usage of medication ("on" [9, 12, 24–27, 30, 31] or "off" [16–18, 21]) or deep brain stimulation [12, 27], the stage of the disease (early-to-mid [9, 16–18], mild-to-moderate [12, 17, 27, 31], moderate-to-severe [25–27, 31]), the ability stand comfortably unaided [12, 25, 27] or to walk independently without a walking aid [12, 16, 24, 27, 29, 31], the absence of serious co-morbidities that could affect gait or balance [25, 29, 30], no other severe neurological, cardiopulmonary or orthopaedic disorders [9, 12, 16–18, 21, 24–27, 29, 31] and that had not undergone functional neurosurgery [31]. Some studies that aimed motor rehabilitation included the presence of bilateral symptoms with impaired postural stability [25, 26] as a criterion. Two of the studies did not present any criteria for the selection of participants with PD beyond the diagnosis of the disease [20, 28], but one of them had the criteria for the participants with HRPD [28].

Table 3: Information about the participants and selection criteria of the studies.

Ref	Participants		Criteria	
	Number	**Scales**	**Inclusion**	**Exclusion**
[17]	12 PD 12 HC	1 - 2.5 H&Y 20 $\pm$ 9.4 UPDRS-III	- H&Y scores of I-III. - Never taken anti-parkinsonian medication.	- Other neurological or orthopedic disorders. - Other impairments that interfere with gait.
[18]	12 PD 12 HC	1.6 $\pm$ 0.5 H&Y 20 $\pm$ 9.4 UPDRS-III	- H&Y scores of I-II. - Never taken anti-parkinsonian medication.	- Other neurological or orthopedic disorders. - Other impairments that interfere with gait.
[9]	13 PD 12 HC	28.1 $\pm$ 11.2 UPDRS	- H&Y scores of I-II. - On-phase of medication.	- Other neurological or orthopedic disorders. - Other condition that could affect balance.
[16]	13 PD 12 HC	1.8 $\pm$ 0.6 H&Y 28.1 $\pm$ 11.2 UPDRS	- H&Y scores of I-II. - Never taken anti-parkinsonian medication. - Ability to walk independently.	- Other neurological or orthopedic disorders. - Other condition that could affect balance.
[28]	13 PD 31 HRPD 13 HC	PD: 26.8 $\pm$ 11 UPDRS-III HRPD: 3 $\pm$ 3 UPDRS-III	HRPD: - Presence of an enlarged area of hyperechogenicity in the mesencephalon on transcranial sonography. - Presence of one motor sign or two risk and prodromal markers of PD	HRPD: - PD diagnosis
[19]	100 PD 50 HC	2 $\pm$ 0.8 H&Y 16.7 $\pm$ 9.2 UPDRS-III	- H&Y scores of I-III.	-
[20]	7 PD 7 HC	-	- Diagnosis of PD.	-

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Table 3 – *Continued from previous page*

Ref	Participants		Criteria	
	Number	**Scales**	**Inclusion**	**Exclusion**
[12]	17 PD 17 HC	2 $\pm$ 0.5 H&Y 35.71 $\pm$ 11 UPDRS-III 2.29 $\pm$ 1.57 PIGD	- H&Y scores of I-III. - On-phase of medication. - Ability to stand unaided.	- Other neurological or orthopedic disorders. - Other condition that could affect balance. - Use of deep brain stimulation. - Use of an assistive device for ambulation.
[21]	13 PD 12 HC	1.8 $\pm$ 0.2 H&Y 26.6 $\pm$ 3.5 UPDRS-III 0.9 $\pm$ 0.4 PIGPIGDD 13 $\pm$ 1.9 Bradykinesia 5.8 $\pm$ 1 Rigidity	- H&Y scores of II. - Off-phase of medication.	- Presence of orthopedic disorders.
[22]	5 PD 5 HC	2 - 3 H&Y	- H&Y scores of II-III.	- Presence of orthopedic disorders.
[29]	7 PD	2.5 $\pm$ 0.5 H&Y	- Ability to walk independently.	- Other neurological disorders. - Other impairments that interfere with gait or balance. - Presence of clinically significant hearing problems.
[30]	20 PD	Feedback / Control group: 17.9 $\pm$ 2.7 / 15.4 $\pm$ 1.1 UPDRS 1.6 $\pm$ 0.1 / 1.6 $\pm$ 0.2 H&Y	- Diagnosis of PD. - On-phase of medication. - Ability to walk independently.	- Other neurological disorders. - Other impairments that interfere with balance.
[24]	10 PD	3 - 4 H&Y >=2 in UPDRS item 33	- Diagnosis of PD. - On-phase of medication.	- Use a wheelchair. - Other neurological disorders.

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Table 3 – *Continued from previous page*

Ref	Participants		Criteria	
	Number	**Scales**	**Inclusion**	**Exclusion**
[25]	11 PD 9 HC	3 - 4 H&Y	- H&Y scores of III-IV. - Bilateral symptoms with impaired postural stability. - On-phase of medication. - Ability to stand unaided.	- Presented severe distal sensory loss or limited ankle range of motion. - Other neurological disorders. - Other impairments that interfere with balance.
[26]	9 PD 9 HC	3 - 4 H&Y	- H&Y scores of III-IV. - Bilateral symptoms with impaired postural stability. - On-phase of medication.	- Other neurological or orthopedic disorders. - Presented severe distal sensory. - Other impairments that interfere with balance.
[31]	153 PD	2 - 4 H&Y	- H&Y scores of II-IV. - On-phase of medication. - Ability to walk independently. - Tremor, rigidity or the bradykinesia score >2.	- Other neurological, cardiopulmonary or orthopedic disorders. - Undergone functional neurosurgery. - Participation in a physiotherapy program two months before the beginning of the study.
[27]	42 PD	Experimental / Physiotherapy: 2.7 ± 0.7 / 2.9 ± 0.5 H&Y 16.6 ± 6.8 / 22.3 ± 7.3 UPDRS-III 46.0 ± 9.3 / 42.1 ± 10.9 BBS	- H&Y scores of II-IV. - On-phase of medication. - Ability to walk and stand unaided.	- Other neurological disorders. - Use of deep brain stimulation.

The experimental protocol during the data acquisition of the selected studies can be divided into three categories:

1) Gait tasks – involves activities such as walking and turning [17–19, 22, 24, 30, 31].
2) Quiet stance – standing upright under altered surface, stance, or vision [9, 12, 16, 21, 24, 29, 30].
3) Dynamic weight-shifting exercises – exercises focused on controlling weight-shifting [20, 25–29].

Depending on these categories, the metrics vary. When the studies' protocol involved gait tasks, the metrics identified included typical gait metrics, such as cadence (step frequency), walking speed, step length, step/stride regularity, step symmetry, time turn-to-sit, turning velocity and peak trunk rotation. If the protocol comprised posture analysis in quiet stance, the metrics considered were sway-associated metrics like jerk - relative smoothness of postural sway, root mean square (RMS) - sway dispersion, mean velocity (MV), centroidal frequency (CF - frequency at which spectral mass is concentrated), frequency of sway (95% power frequency - F95), normalized path length and peak-to-peak (amplitude displacement). In protocols with dynamic weight-shifting exercises, the metrics comprised AP (anterior-posterior)/ML (medial-lateral) limit of stability (LOS), angular displacements, velocities and movements of the CoM of the body.

Salarian et al. [17, 18] proposed an instrumented version of the Timed Up and Go (TUG) test (iTUG), studied its sensitivity to the pathology, by identifying mobility deficits in subjects in early stages of PD and with no apparent impairments in motor performance, [17] and tried to find a correlation between iTUG components and the disease severity [18]. These studies revealed that, compared to HC, PD subjects exhibit slow turning and arm swing and a decreased cadence and trunk rotation, even though the traditional TUG test did not differentiate the two groups. Furthermore, they were able to find a significant correlation between some of the most discriminatory parameters (peak arm-swing velocity, cadence and average turning velocity) and motor UPDRS total score and sub-scores (gait/posture, bradykinesia and rigidity). These findings showed that the impairments in mobility differed between individuals with PD (i.e., a subject with decreased arm swing could have a cadence comparable to HC) and because of that TUG is an adequate test since it involves different gait tasks and postural transitions. It is noteworthy that these studies presented a new mathematical model to detect turning during gait that is not sensitive to noise or artifacts and can even detect very slow or quick turns, as opposed to the traditional angular velocity threshold methods.

Mancini et al. [9, 16] used wearable sensors to measure postural control during quiet stance to distinguish PD patients in early stages of the disease with no signs of balance problems from HC and compared the postural sway measures of the wearable sensors to those obtained from a force platform. Additionally, the sway measures were compared with clinical scales [9]. The studies concluded that the parameter which best discriminated PD from HC was jerk. PD participants presented higher values of jerk due to frequent postural corrections, which may reflect increased trunk axial rigidity. Besides that, they showed a larger RMS and MV and a lower CF. The studies also verified that these metrics were just as sensitive as the acquired from the force platform to differentiate the two groups, Figure 4. However, they failed to find a significant correlation with UPDRS and UPDRS-III scores and were not surprised with this result since these scores only contain one item that evaluates postural stability (the pull test) and UPDRS-III is also related to bradykinesia, rigidity and tremor. Nonetheless, several metrics, like jerk, RMS, MV and total power, correlated considerably with PIGD (sub-score of UPDRS-III – sum of the four items related to posture, gait, sit-to-stand and pull test).

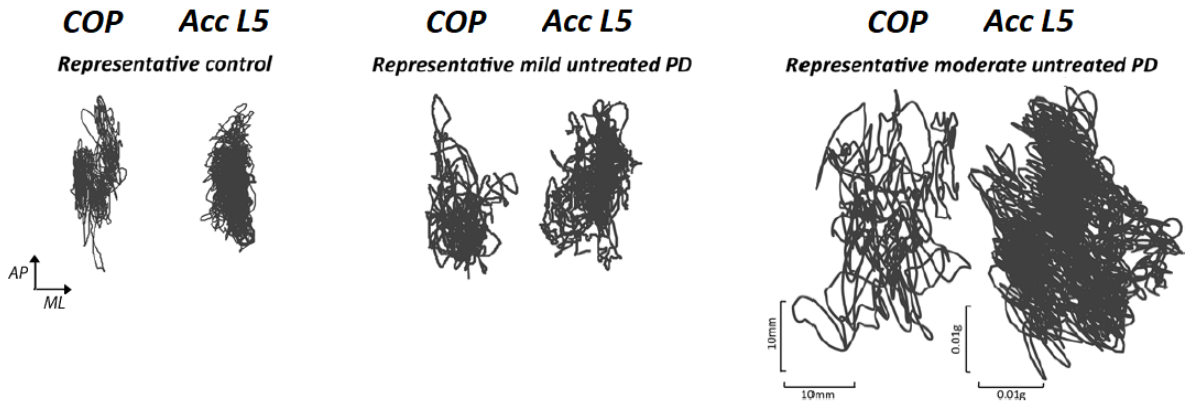

Figure 4: CoP and Acc traces of a HC, a mild and a moderate untreated PD subject. Adapted from [9].

Hasmann et al. [28] implemented an instrumented version of the functional reach (FR) test (iFR) to verify if this test can distinguish PD patients from HC and to discover if it can also discriminate HRPD from these groups, so it can be used as a biomarker in the prodromal phase of the disease. An advantage of this test is that two parameters can be considered in the evaluation: FR distance and "behaviour" (a participant can achieve a greater distance due to motivation and, because of that, have poor sway metrics and *vice versa*). The study showed that PD participants had a decreased FR distance and AP/ML accelerations which are related to increased muscle rigidity that leads to inadequate compensatory motor response, and to the strategy chosen to maintain balance (the PD group tends to adopt a hip strategy while the HC group picks

an ankle strategy that mainly affects AP metrics). These three metrics and jerk were included in a model to differentiate HRPD from the two groups, which revealed that a set of metrics was better for recognizing HRPD than any single metric.

Hannink et al. [19] explored if peak accelerations in the vertical direction during landing and along movement direction during the loading phase, Figure 5, acquired with wearable sensors on the feet while walking, can serve as novel markers to characterise postural instability and provide separation between HC, subjects with PD with postural instability (pull test > 0) and without (pull test = 0). These parameters can evidence a cautious behaviour of the subject while walking by evaluating the intensity of the impact during the foot landing and the stride initiation. This is associated with postural stability since higher accelerations during these phases demand rapid postural control responses. The study concluded that the markers extracted can detect postural instability and discriminate HC and both PD groups. Compared to PD subjects without postural impairments, posturally impaired PD subjects present a 14% and 24% decrease of the peak acceleration during loading and landing, respectively.

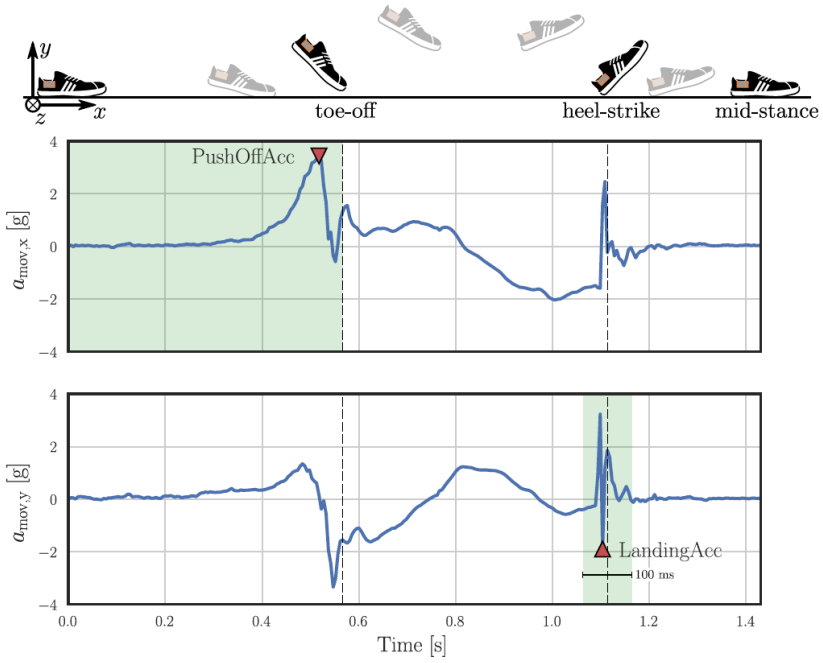

Figure 5: Representation of the peak accelerations during loading and landing. Taken from [19].

Phan et al. [20] studied the difference in flexibility or back rigidity to identify participants with PD amongst HC by detecting the time delay between a sensor in the upper back and another in the lower back during the pull test. The study revealed that individuals with PD exhibit a significantly longer delay (usually, higher

than two seconds while for HC is less than a second) and therefore it is possible to distinguish the two groups through this metric.

Ozinga et al. [12] used a mobile device to capture the movement of the CoM (in 3D) and sway measures during quiet stance in six different balance conditions (altered surface, stance, and vision) in order to quantify postural stability and separate HC from participants with PD. The parameters obtained with the mobile device were compared with those acquired from a motion capture system. Moreover, they tried to find a correlation between the sway metrics and UPDRS-III score and sub-scores. The study verified that the sway metrics presented significant differences between the two groups, and the movement of CoM increased in volume with the difficulty of the tasks in both groups but was consistently larger in PD participants, Figure 6. This way, the volumes created with the movement of CoM allow to single out difficulties of patients regarding the visual, vestibular and/ or somatosensory systems. This information can be useful for diagnostic purposes or treatment management. Furthermore, the tablet proved to be as accurate and valid as the motion capture system. However, no correlation was found between sway metrics and UPDRS-III score or sub-scores. This can be explained by the lack of elements related to postural stability in these evaluations.

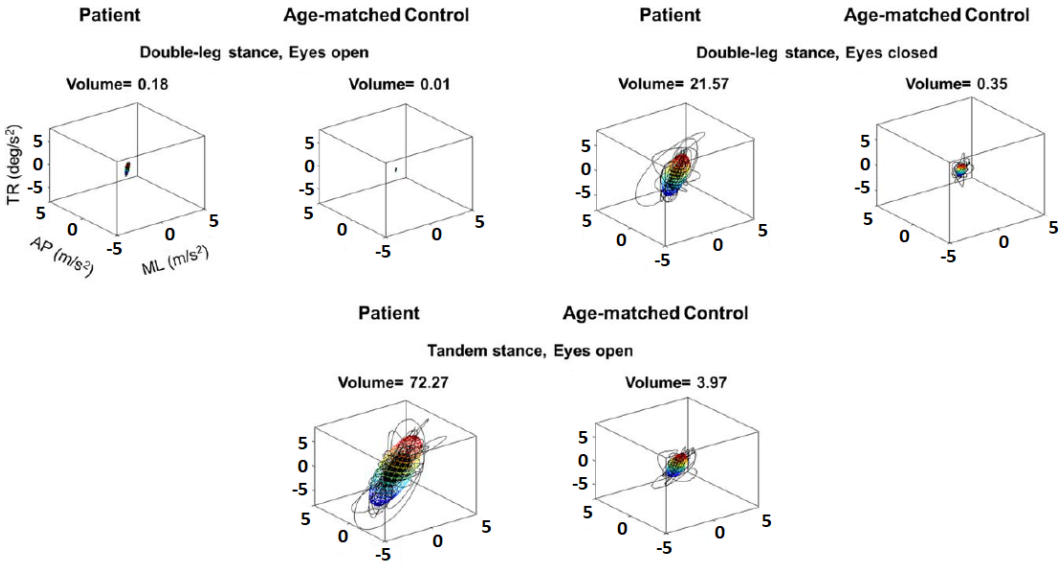

Figure 6: Movement of CoM of a patient and a HC (in three balance conditions). Adapted from [12].

Mancini et al. [21] intended to study the disease progression over the course of a year by analysing changes in postural sway through metrics already proven to be efficient in differentiating PD patients in

early stages of the disease from HC. It was observed a decline of the sway metrics over the year (i. e., an increase in ML jerk, sway dispersion, velocity and frequency), even though there were almost no changes in UPDRS-III score and sub-scores. Therefore, the study concluded that sway metrics are more sensitive to disease progression than motor scores used in clinical settings. In addition, they verified that ML sway measures were more useful than AP since sway in the ML direction requires a more prominent involvement of the hips and trunk muscles, which are usually more affected in PD, whereas sway in the AP direction resorts a bit more to the ankles.

Yang et al. [22] evaluated the efficiency of an autocorrelation system to estimate gait parameters in real-time by attempting to discriminate individuals with PD from HC. Compared to HC, PD participants revealed a walking pattern less regular, with fluctuations and smaller peak magnitudes, steps not as symmetric while walking at a higher speed and an increased cadence, Figure 7. Hence, it was possible to separate the two groups. This study also showed that, while walking, the ML component was not as sensitive to mobility deficits as the AP and VT (vertical) components.

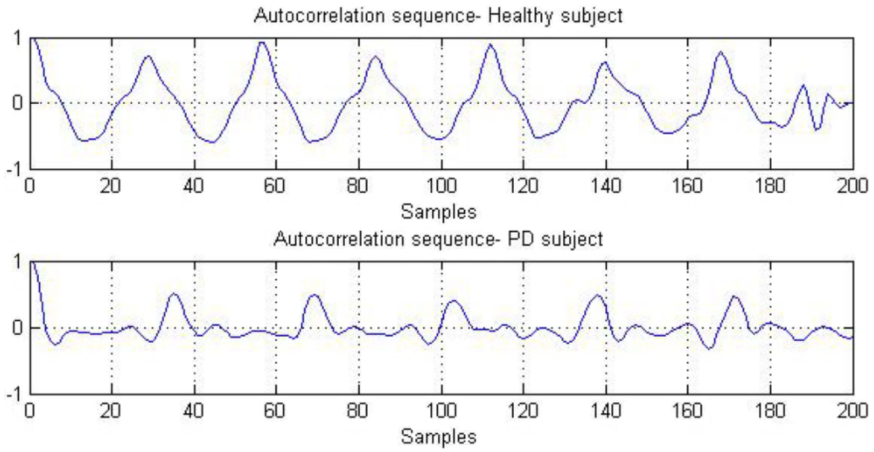

Figure 7: Autocorrelation sequence for for a HC and a PD patient. Taken from [22].

Mirelman et al. [29] investigated if audio biofeedback can positively affect postural stability and if the results are still discernible after a month without training. The training consisted of 18 sessions (6 weeks) of static and dynamic balance exercises with biofeedback (with sounds that were modulated in frequency and amplitude). An evaluation involving several clinical tests (BBS, TUG, UPDRS, chair rise test) was performed at baseline and a week and a month after the training sessions. These evaluations showed that, although

subtle, the differences in the balance control measurements were positive both post-training and at one month follow-up.

Nanhoe-Mahabier et al. [30] conducted a research to discover if biofeedback training with vibrotactile cues can enhance postural control. To prove this, the PD participants were separated into two groups in order to compare the results of training (comprising gait and stance tasks) with and without providing feedback about trunk sway. The training included six tasks, while the evaluation, performed before and after the training, consisted of 12 to verify if the biofeedback training has carry-over effects. Results showed a substantial reduction of roll and pitch sway angular velocity (mainly in the AP direction) in the PD group that received biofeedback during training, comparably to the other group, meaning the training with biofeedback is a better option to improve balance. Additionally, these parameters were also decreased in tasks not included in the training, which implies that biofeedback training provides short-term carry-over effect.

Rossi-Izquierdo et al. [24], similarly to [30], evaluated the effect of balance training with vibrotactile biofeedback in postural stability. The study implemented a daily training over 2 weeks which consisted in the completion of 6 stance and gait tasks (from Standard Balance Deficit Test - SBDT) while receiving feedback in the directions that presented values of sway higher than the predefined thresholds. Note that, the vibration frequency increased with the deviation to the threshold values. The evaluation, consisting of SBDT, Sensory Organization Test (SOT), Dizziness Handicap Inventory (DHI), Activity-specific Balance Confidence (ABC) scale and number of falls over the past three months, was carried out at baseline, immediately after the 2 weeks of training and three months after its finish. The study revealed substantial improvement in all the measures made in the evaluation, both post-training and at three-month follow-up, with exception of the SBDT tasks that were not included in the training. This demonstrates that balance training with vibrotactile biofeedback promotes postural stability and these effects are noticeable up to, at least, three months after stopping the training. However, no signs of carry-over effect were found.

Lee et al. [25] explored the use of different types of external cues to provide biofeedback to PD patients while performing dynamic weight-shifting exercises. During the exercises the participants had to shift their weight to try to accompany a slow-moving target in the ML and in the AP direction, Figure 8, and received feedback about their relative position to the target through visual and/or vibrotactile cues. The vibrotactile biofeedback provided was binary (the motor tactors were either ”on” or ”off”) and the tactors activated when the position error of the participant to the target surpassed a certain value. The visual biofeedback consisted

on a representation of the position of the body in relation to the target. Prior to and after the exercises the LOS in the AP and ML direction was acquired for all the participants (which included a group of individuals with PD and a HC group). Results demonstrate that visual and vibrotactile biofeedback have similar effects and that multimodal biofeedback (visual and vibrotactile) was the strategy that had a more significant impact on the participants' performance of the exercises, since they were able to get a considerably lower position error. Moreover, all the individuals included in the study showed improvements in the LOS after the completion of the training, which shows an improvement in postural stability.

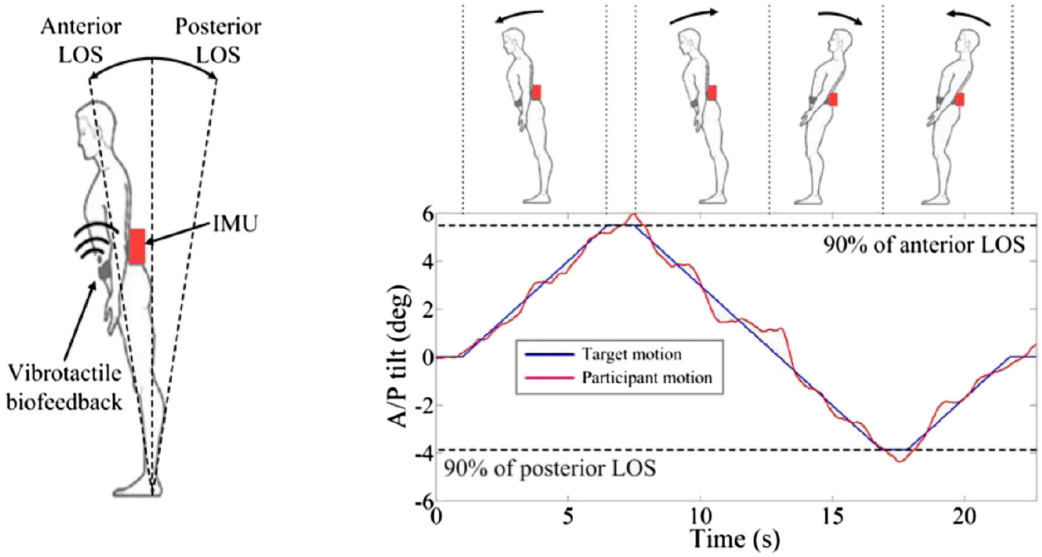

Figure 8: Representation of the sensor and tactors location and of the data from a dynamic weight-shifting exercise in the AP direction. Adapted from [25].

Lee et al. [26] continued the study previously discussed and implemented the same exercises, this time only with vibrotactile cues, to evaluate the impact of a binary versus a continuous coding scheme. Once more, the study included a group of individuals with PD and a HC group, and the LOS was acquired before and after the dynamic weight-shifting exercises. The difference of the continuous coding scheme to the binary was that the vibration frequency increased with the position error of the participant to the target. The continuous coding scheme proved to be a better option as it was able to provide a better outcome in the exercises. This type of coding scheme provides the participants information about the error magnitude, thus, allowing them to correct more easily their position. In addition, once again, both groups increased the LOS both in the AP and ML direction after concluding the exercises and, in both studies, it was possible to distinguish these two groups as the PD participants' performance in the exercises was significantly worst.

Rochester et al. [31] evaluated the influence of external cues during training, on motor learning. The training lasted three weeks and involved walking and turning with or without a tray containing two cups filled, while receiving either visual, auditory, vibrotactile or no cues. The additional sensory information consisted in a set of rhythmic cues (sounds, light flashes or pulsed vibrations) to which participants were asked to synchronize their gait. These exercises were repeated six weeks after the completion of the training to perceive if the biofeedback effects were retained. The study revealed an improvement in walking speed and step length which was retained, and that there were no major differences between the different types of cues during the training.

Carpinella et al. [27] investigated the efficacy of a system that provides both visual and auditory biofeedback regarding trunk inclination and position of CoM on postural stability and gait rehabilitation. The protocol incorporated a 20-session training that comprehended static (quiet stance in several conditions), quasi-dynamic (weight shifting exercises) and dynamic (walking over obstacles) tasks, and an evaluation, which incorporated the BBS and 10MWT, that was performed at baseline, post-training and a month after stopping the training. The PD participants were divided into two groups, and while both groups completed the training, only one received biofeedback. Results showed a substantial and positive difference in BBS scores, post-training and at one month follow-up, of the group that received biofeedback during training in comparison to the other group, which indicates that biofeedback can enhance balance performance and is better than physiotherapy.

Table 4: Goal, protocol, metrics and results of the WDPA.

Ref	Goal	Relevant Metrics	Protocol	Data Analysis	Relevant Results
[17]	Diagnosis	- Cadence - Angular velocity of arm-swing - Time turn-to-sit - Turning velocity	TUG test	Comparison between groups	- Compared to HC, PD subjects presented turning velocity, angular velocity of arm swing, cadence and trunk rotation, even though the traditional TUG test did not differentiate them. - The most reliable subcomponent of the test was gait and cadence its most reliable metric. Duration of turns was the most reliable turning metric. PD subjects performed normally in sit-to-stand.
[18]	Disease severity	- Cadence - Angular velocity of arm-swing - Time turn-to-sit - Turning velocity - Peak trunk rotation	TUG test	Correlation of metrics to UPDRS-III and sub-scores	- The Motor UPDRS correlated significantly with arm swing, cadence and turning parameters. Turning velocity correlated significantly with bradykinesia and Gait/Posture sub-scores, and peak trunk rotation velocity correlated considerably with rigidity. - Impairments in mobility vary between PD subjects.
[9]	Disease severity	- Jerk - RMS - MV - CF - Total power	Stand upright with EO	Comparison between groups	- Untreated PD subjects compared to HC showed RMS, MV and jerk. - No significant correlation was found between sway metrics and UPDRS-III Score. Several measures showed a considerable correlation with the PIGD.
[16]	Diagnosis	- Jerk - RMS - MV	Stand upright with EO	Comparison between groups	- Postural control is impaired in subjects with untreated PD, even when it is not clinically apparent. - Jerk was the parameter that best discriminated postural sway between the groups.

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Table 4 – *Continued from previous page*

Ref	Goal	Relevant Metrics	Protocol	Data Analysis	Relevant Results
[28]	Diagnosis	- Jerk - FR distance - AP and ML acceleration	FR test	Comparison between groups	- PD patients differed from HC in the following parameters: FR distance, AP and ML acceleration. - A set of metrics of the iFR separated HRPD better from HC than any single metric.
[19]	Diagnosis	Peak acceleration during loading and landing	4x10 meters-walk (40MW)	Comparison between groups	- The parameters extracted can detect postural instability and provide a separation of HC and both PD groups since they are reduced in PD patients and even more so if they have postural instability.
[20]	Diagnosis	Back flexibility (delay between two sensor angular velocity signals)	Pull test	Comparison between groups	- PD patients can be identified amongst controls since they exhibit significantly longer delays.
[12]	Diagnosis and Disease severity	- Normalized path length - RMS - Total power - Peak-to-peak (amplitude displacement)	6 balance conditions under altered surface, stance, and vision	Comparison between groups	- Sway metrics presented significant differences between the two groups, and the movement of CoM increased in volume with the difficulty of the tasks in both groups but were always larger in PD participants. - The tablet proved to be as accurate and valid as the motion capture system. - No correlation was found between sway metrics and UPDRS-III score or sub-scores.
[21]	Disease progression	- Sway dispersion (RMS) - Sway velocity (MV) - Frequency of Sway (F95) - Jerk	Stand upright for 2 min	Comparison between groups	- Objective sway measures depreciate over the course of a year (i. e., □ in ML jerk, sway dispersion, velocity and frequency) even though there were almost no changes in UPDRS-III score or sub-scores. - ML sway measures were more sensitive than AP to disease progression.

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Table 4 – *Continued from previous page*

Ref	Goal	Relevant Metrics	Protocol	Data Analysis	Relevant Results
[22]	Diagnosis	- Cadence - Step regularity - Stride regularity - Step symmetry	5-meter-walk test (5WMT) x3	Comparison between groups	- It was possible to separate the two groups since PD participants revealed a walking pattern less regular, with fluctuations and smaller peak magnitudes, steps not as symmetric while walking at a higher speed and an increased cadence. - While walking, the ML component was not as sensitive to mobility deficits.
[29]	Rehabilitation	Trunk inclination and accelerations	Training: static and dynamic balance exercises; Evaluation: BBS, TUG, UPDRS, chair rise test	Comparison of initial and final results	- Although small, the differences in the balance control measurements were positive both post-training and at one month follow-up (especially in TUG, time sit-to-stand, BBS - mostly in items 12 and 13, UPDRS-III - with changes in the pull test)
[30]	Rehabilitation	- 90% range of sway angle and sway angular velocity in the roll and pitch plane - Task duration	6 gait and stance tasks for training and 12 for the evaluation	Comparison of initial and final results and between groups	- Substantial reduction of roll and pitch sway angular velocity (mainly in the AP direction) in the PD group that received biofeedback during training, comparably to the other group. - These parameters were also decreased in tasks not included in the training (biofeedback training provides short-term carry-over effect).
[24]	Rehabilitation	Body sway in the roll (ML) and pitch (AP)	Training: stance and gait tasks; Evaluation: SBDT, SOT of CDP, DHI, ABC scale and number of falls	Comparison of initial and end results	- Considerable improvement in all the measures made in the evaluation, both post-training and at three-month follow-up, with exception of the SBDT tasks that were no included in the training (no carry-over effect).

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Table 4 – *Continued from previous page*

Ref	Goal	Relevant Metrics	Protocol	Data Analysis	Relevant Results
[25]	Rehabilitation (and Diagnosis)	- AP/ML angular displacements - AP/ML velocities - AP/ML LOS	Dynamic weight-shifting exercises	Comparison of initial and end results and between groups	- Visual and vibrotactile biofeedback have similar effects and multimodal biofeedback (visual and vibrotactile) was the strategy that had a bigger impact on the participants' performance of the exercises (a considerably lower position error). - Both groups showed improvements in the LOS after the completion of the training.
[26]	Rehabilitation (and Diagnosis)	- AP/ML angular displacements - AP/ML velocities - AP/ML LOS	Dynamic weight-shifting exercises	Comparison of initial and end results and between groups	- The continuous coding scheme was able to provide a better outcome in the exercises. - The groups increased the LOS both in the AP and ML direction after concluding the exercises. - HC had significantly better performance than the PD group.
[31]	Rehabilitation	- Gait speed - Step length	Walk 6m x2 and turn (with and without a tray)	Comparison of initial and final results	- Improvement in walking speed and step length which was retained. - No major differences were found between the different types of cues during the training.
[27]	Rehabilitation	- AP/ML trunk angular displacements - AP/ML movements of body CoM - Knee flexion angle	Training: Exercises focused on controlling weight-shifting; Evaluation: BBS, 10MWT	Comparison between groups	- There was a substantial and positive difference in BBS scores, post-training and at one month follow-up of the group that received biofeedback during training in comparison to the other group.

2.4 Discussion

2.4.1 How have the WDPA been applied in PD?

Depending on the underlying goal, the WDPA developed in the past 12 years to quantify postural stability in PD can be divided into three categories: (i) **diagnosis**, if the data was used to identify individuals with postural impairments; (ii) **disease severity/progression**, when there was an attempt to correlate the measures to clinical scales and/or an analysis of the evolution of these measures over time in a patient; and (iii) **rehabilitation**, if the device was used to improve postural control by providing meaningful cues. It can be observed by Figure 9 that there are a similar number of studies that aimed to used WDPA to help in PD diagnosis and rehabilitation. These goals are relevant for the clinical environment to perform more objective evaluations and enhance treatment but there is **still a need for further investigation with more clinical evidence** since it was considered that most studies presented a small sample size, despite the promising results.

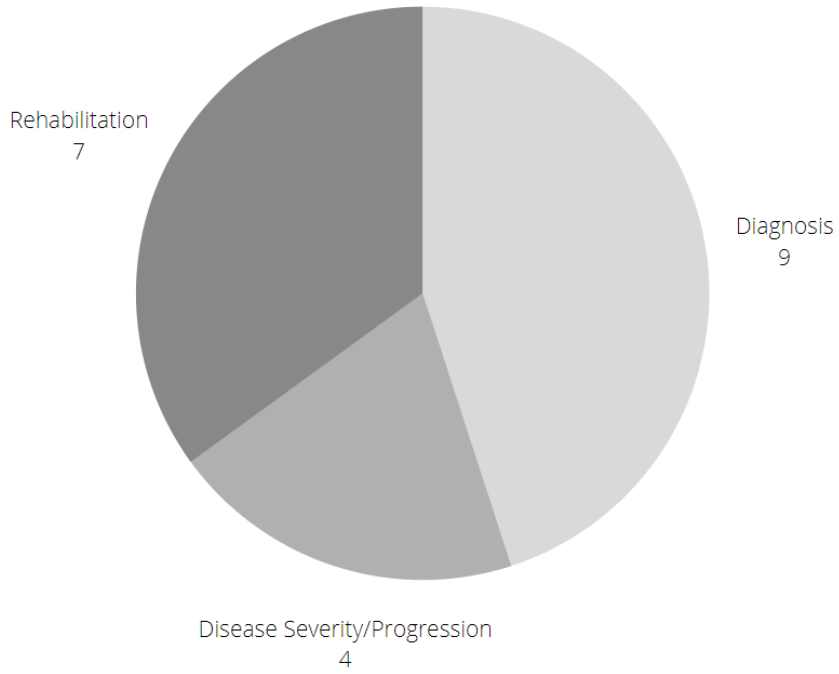

Figure 9: Purpose of the selected studies.

2.4.2 Which technologies were integrated in the WDPA, what are their setting parameters and where were they placed within the body?

The sensors integrated in the WDPA were used to collect information about the movement of the body in an attempt to obtain metrics capable of characterizing postural stability. This data can **improve diagnosis, eliminate the subjectivity of many clinical examinations** performed to assess the stage of the disease, which is **relevant to manage treatment**, or even **detect patients at a higher risk of falling** earlier in the disease [2, 19].

The sensor most frequently applied was the IMU, which can combine three sensors (accelerometers, gyroscopes and magnetometers). The studies that did not use IMUs employed one or more of its components. Table 5 summarizes the outcomes of the IMU components. These kinds of sensors present an affordable, lightweight and portable solution that allows long continuous monitoring, as they present low-power consumption, and are able to capture body movement in three dimensions. On the other hand, usually, the data acquired through these sensors needs to be pre-processed so it can supply meaningful measures [9, 12].

Table 5: Outcomes of the sensors integrated in the WDPA in the past twelve years.

Sensor Type		**Outcome**
IMU	Accelerometer	Linear acceleration
	Gyroscope	Angular velocity (raw, pitch and yaw)
	Magnetometer	Direction (absolute angular movements relative to the Earth's magnetic field)

The number of sensors included in the devices varied between 1 and 7. More sensors represent more information, but also a bulkier and heavier system with increased complexity. Since some of the most desired features in a wearable are to be light, have a quick set-up and place minimum constraints on the subject, the majority of the studies chose to implement only 1 or 2 sensors in the device.

As observed in Figure 10, the sensors were placed in several locations of the body, although the lower back was certainly the most commonly selected. Lower back inertial data enables to capture information regarding the CoM of the body, which is directly related to postural reflexes. For the most part, studies that used more sensors and chose other locations for them, such as the legs or the feet, were the ones that

involved gait tasks for the data acquisition in order to identify mobility deficits [17, 18, 31]. However, by using one inertial sensor on the lower back, it is possible to obtain a complete analysis of the gait cycle, not requiring the use of two sensors in each lower limb and needing less computational power for data processing [32].

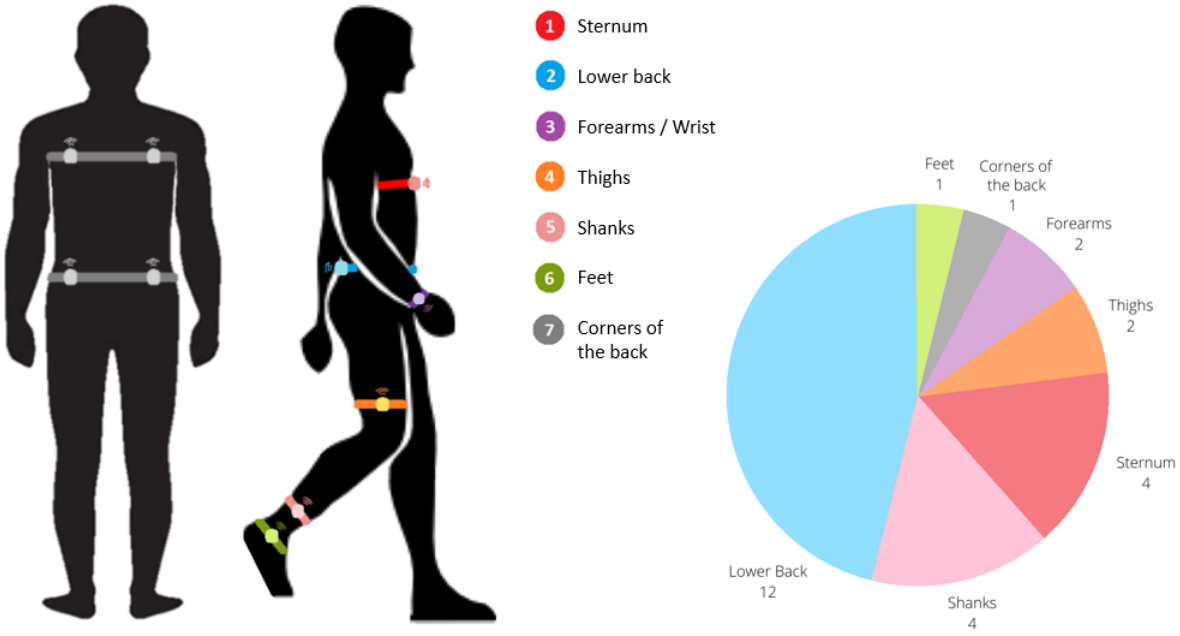

Figure 10: Sensor location.

Besides a sensory system, some of the devices included an actuation system to provide additional sensory information to the user in order to enhance postural control and/or walking stability. These systems could improve the existing rehabilitation programs, be used in exercises to practice at home or even as an assistive device [33].

The actuation systems provided biofeedback through either visual, auditory, vibrotactile or even multi-modal cues. The studies revealed that cued training has a positive effect on postural control, although no major differences were found between these types of cues in enhancing motor performance [25, 31]. However, **biofeedback training with more than one type of cues was reported to have a more significant impact on the participants' postural stability** [25]. Despite these results, some studies emphasize the advantages that vibrotactile cues exhibit when compared to the others, such as being small, portable and having low-power consumption, making them suitable for wearable systems. Also, it is indicated that vibrotactile actuation systems possess characteristics that make them appropriate for use outside

the clinical setting, like the ability to be concealed under clothes, not constraining the user movements or interfering with their visual or auditory fields [26].

Regarding the devices that provided vibrotactile cues, the preferred configuration for the tactors was four situated on the front, back and sides of the waist. This enabled users to perform postural adjustments with intuitive information about the direction in which the correction has to be made. Another approach was employing eight motor tactors around the head in an attempt to decrease delays in sensory transmission [30]. Furthermore, vibrotactile cues can possess a binary or a continuous coding scheme. Lee et al. [26] evaluated the impact of these coding schemes and verified that the **continuous coding scheme allowed participants to correct their movements more easily** since it provided information about the error magnitude.

Throughout the articles that aimed motor rehabilitation, biofeedback was used as a mean to indicate that certain parameters were out of the accepted range, with the exception of one of the articles which used it to assist the performance of an exercise, in this case, by providing rhythmic cues for participants to synchronize their gait [31].

2.4.3 How have WDPA been clinically validated in PD?

The protocols, the type of participants comprised and the strategy to evaluate the effectiveness of the systems differed according to the study's purpose.

In case the articles aimed to use WDPA for PD diagnosis, the study included both patients with idiopathic PD, usually in early stages of the disease and with no apparent motor symptoms, and a group of HC. The protocol consisted in acquiring data while performing a specific clinical examination or exercise, that could involve walking, turning, weight-shifting or standing upright in different vision, surface or stance conditions. Data analysis was accomplished by comparing the metrics obtained from PD patients and the HC group.

Considering the investigations that studied disease progression or severity using technologies for postural assessment, these also comprehended a group of HC and another of PD patients, in early stages of PD to study the progression of the disease over time or patients in several stages of PD to correlate metrics collected to scales that evaluate the severity. The protocol involved collecting data while performing specific motor exercises, and an evaluation to perceive the stage of the disease and the degree of some motor impairments. In case the article analysed the disease progression [21], the protocol included follow-up

sessions, where the study was repeated various times over a certain period. The last step of these studies consisted in trying to find a correlation between the metrics and the scores from the evaluation. It is noteworthy that some of the studies that captured sway measures compared them to the obtained from a force platform [9] or a motion capture system [12] to support the experimental validity of the metrics acquired from the wearable sensors.

Regarding studies that aimed to use WDPA for motor rehabilitation, the vast majority only included PD patients, which, depending on the paper, varied from milder to a more severe stage of the disease. The protocol comprised one or more sessions of cued training and an evaluation that was performed at baseline, post-training and, in some studies, a few weeks or months after the last training session (to perceive if the biofeedback effects were retained). The evaluation was either done with clinical scales or by repeating the exercises performed during the training to verify if there was an improvement in the scores or metrics acquired, respectively. Two of the articles even implemented more exercises on the evaluation so it was possible to determine if cued training provides carry-over effect [24, 30]. Furthermore, two other studies separated the PD participants into two groups to compare the differences between training with and without biofeedback [27, 30].

Results concerning diagnosis revealed that it is possible to collect objective measures from gait, turning, sway and clinical tests to distinguish individuals with PD from HC, even if these are in very early stages of the disease and present no evident impairments in motor performance, since these exhibit decreased postural responses.

Moreover, a study found a correlation between gait and turning metrics and UPDRS-III score and sub-scores (gait/posture, bradykinesia and rigidity) [18], and another one was able to correlate sway parameters to PIGD, but not to UPDRS or UPDRS-III as these contain only one item to evaluate postural stability [9]. Mancini et al. [21], which studied the disease progression over the course of a year, concluded that sway metrics are more sensitive to disease progression than motor scores used in clinical settings, as they were able to detect a decline in postural stability despite minimal changes in UPDRS-III scores and sub-scores. In addition, two studies that captured sway measures with wearable sensors verified that these were as valid and accurate as the collected from a force platform [9] or a motion capture system [12].

In regard to cued training, the studies confirmed that visual, auditory and vibrotactile biofeedback could enhance overall stability [24–27, 29–31] and these effects could still be detected at least one to three

months after stopping the cued training [24, 27, 29, 31]. Additionally, the two studies which investigated the carry-over effect reached opposite conclusions, despite all the similarities in their protocols [24, 30]. A possible reason is the difference in participants selection as the individuals in the study that verified carry-over effect [30] were in a more advanced stage of the disease.

2.5 Conclusions and Future Perspectives

Based on the findings reported regarding the use of wearable technology to assess postural responses and provide additional sensory information in order to improve postural control, some highlights and limitations of the current state-of-the-art were gathered.

The sensory system was often comprised by IMUs, and the preferred configurations were one sensor placed in the lower back (near the body's CoM). The data collected made possible the acquisition of postural-related metrics capable of (i) providing a separation of individuals with PD from a group of HC, (ii) distinguishing PD patients with different levels of balance and gait impairments, and (iii) the study of disease progression.

For WDPA integrated on biofeedback devices, the actuation systems provided visual, vibrotactile, auditory or multimodal cues during the exercises, mainly through negative reinforcement. Although results in improving balance through these three types of cues were similar, some of the articles stated that the **vibrotactile biofeedback presented more advantages** [24, 26]. The most adopted configuration for this type of biofeedback were 4 tactors around the waist (front, back, left and right) with either a binary or a continuous coding scheme (even though the continuous coding scheme revealed to be more effective in correcting the participants' movements). The studies revealed that cued training could enhance balance and walking stability, and these improvements are still discernible after a few months.

Even though it is not easy to compare the different configurations of the technologies supporting WDPA, some parameters should be taken into account while designing these devices, such as the desired outcomes and the **users' comfort and acceptability**. With that in mind, the devices should **integrate as little technology as possible, without losing relevant information**, and the sensors and actuators should have the same location to obtain **wearable devices more compact, light and quick and easy to set up**. These are key features for the device to be integrated into a patient's daily life. Additionally, end-users, both patients and clinicians involved, will benefit from a unique device able to provide postural assessment

to analyse the several disease stages, and able to use the postural metrics to provide customized sensory cues. Clinicians and related community will have access to continuous and objective information about the postural conditions of their patients, making these devices a support clinical decision tool. The same device that can measure postural metrics, will be able to be used in rehabilitation centers or patients' homes to provide personalized biofeedback.

Despite the observed significant scientific contribution of the state-of-the-art to a more accurate evaluation and effective rehabilitation of PD patients, there is a need for more clinical evidence, being also required to increase the number of participants in clinical studies.

Regardless of the investigation's goal, **no study was validated on (near) home-based conditions, not reliably repeating the daily tasks of patients**. The inclusion of these tasks, such as lifting bags (e.g., in a supermarket) or walking on stairs/ramps, would benefit patients in terms of motor assistance and rehabilitation by considering functional tasks more similar to their daily context. Also, **the validation of the systems should be more personalized and user-centered**, which would allow WDPA functionalities to address users' requirements. Further, research will benefit from an assessment of device acceptability and usability analysis.

Table 6 summarizes the identified limitations regarding technological, adopted strategies, and validation methodology issues. It is also provided guidelines for their mitigation based on [34], to support user-centered design of medical devices.

Table 6: Limitations identified regarding the WDPA in PD, end-users' requirements and guidelines.

Limitations	**End-users' requirements**	**Guidelines**
Sensors/actuators with different configurations (number and body location)	Portability, comfort, easy set-up	Decrease the number of sensors/actuators and integrate them in a single device
No clear strategy to provide biofeedback	Improvements in overall stability	Investigate metrics in different dynamic activities capable of assessing postural instability
No validation on (near) home-based conditions or inclusion of daily motor tasks	Personalized treatments	Perform experimental tests including daily tasks in home-based scenarios.

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Table 6 – *Continued from previous page*

Limitations	**End-users' requirements**	**Guidelines**
No performance of usability tests	Acceptability of the device	Include the users' opinion in the development of the device and assess its acceptability and usability analysis

3

SOLUTION OVERVIEW

Due to the subjectivity and lack of sensitivity of many clinical examinations, there has been a growing interest in performing instrumented analysis for a more objective assessment of health-related outcomes. Technology-based devices may complement the clinical examination as they enable the acquisition of unbiased measurements and a long-term follow-up on previous outcomes, which allows to detect subtle changes that would normally go unnoticed. Therefore, one of the goals of this dissertation was to create an APP to quantify gait and balance deficits and to provide a more objective assessment of the pull test score.

There is an increasing number of studies being conducted to reduce the subjectivity of the evaluation of movement disorders in different diseases, including PD. One research used the IMU from a mobile phone to characterise the tremor of the hands in PD patients and attempted to correlate the features acquired to the score of the UPDRS-III section related to tremor [35]. Another study developed a smartphone application to collect data and quantify the severity of bradykinesia in PD patients while performing some tasks from the UPDRS-III [36]. However, based on the information gathered, no other study developed an APP to assess postural instability.

To address the main goal of this dissertation, which consists in the design, development and validation of a postural assessment tool that enables more objective and continuous evaluations during dynamic tasks, three objectives were outlined:

(i) Estimation of relevant features for postural stability assessment from inertial data collected during dynamic motor tasks with a wearable device;

(ii) Identification of critical metrics able to serve as a biomarker for the postural instability level in PD and that present a correlation with one or more clinical scales;

(iii) Implementation of an AI-based algorithm to increase the objectivity of postural instability assessment under dynamic conditions (and integration of this algorithm on a user-friendly APP).

To this end, a wearable motion device was used to collect the inertial data under dynamic motor conditions. Since this dissertation was integrated into the +sense project, it was used a wearable technology from +sense capable of collecting inertial information regarding the CoM. Further, this dissertation contributes to +sense project with new scientific knowledge about postural assessment in PD. Ergo, this chapter contains an overview of the components and methods used in this dissertation to acquire and process the data, starting with an introduction to the +sense project and an explanation of how this dissertation contributed to the project (including a description of the APP developed), followed by the experimental protocol used for collecting the data and finishing with the data analysis performed.

3.1 +sense

This dissertation was incorporated and intended to contribute to the +sense project. The main aim of the +sense project is to enhance the quality of life of patients by promoting motor autonomy while reducing their reliance on third parties. For that purpose, the project offers front-end personalized high-tech solutions based on wearable devices capable of acquiring patients' sensorimotor information, which combined with artificial intelligence algorithms allows to interpret the data and provide valuable and personalised feedback. There are four +sense modules, as shown in Figure 11: (1) +sBiofeedback; (2) +sMotion; (3) +sC-support; and (4) +sImmersive. In particular, the development of this dissertation aimed to have an impact on the +sMotion and +sC-support.

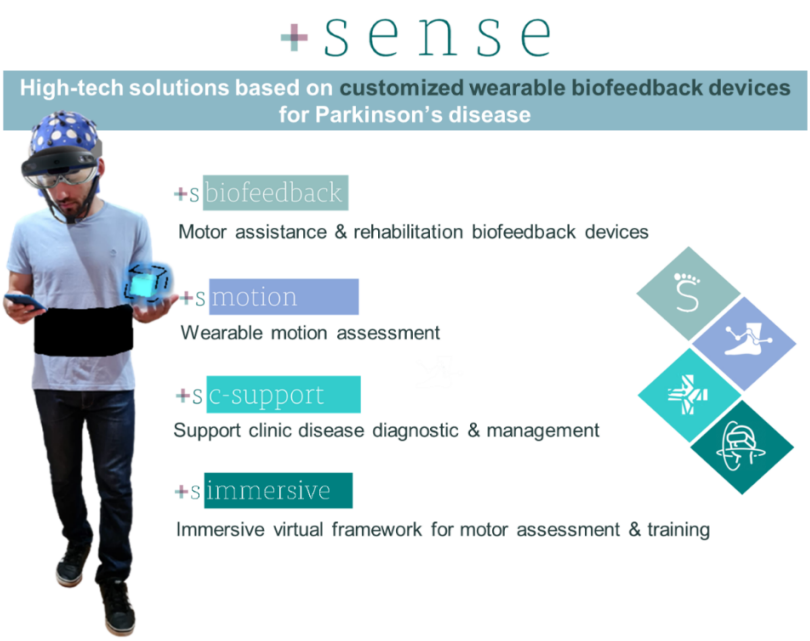

Figure 11: Four modules of the +sense project.

3.1.1 +sMotion

The +sMotion module was designed to collect and monitor inertial data from the lower trunk, perform gait segmentation in real-time, post-process these signals and estimate gait-associated metrics. Therefore, this module makes use of an instrumented waistband, conceived to easily adapt to different users' physiognomies, that includes a gait analysis LAB, depicted in Figure 12. Thus, this module comprises:

1) **Sensory Acquisition Unit** - collects acceleration and angular velocity data through an inertial measurement unit (MPU-6050).
2) **Processing Unit** - consists of a STM32F4-Discovery responsible for receiving the data acquired and detecting gait events (heel-strike, foot-flat, mid-stance, toe-off and heel-off) using an algorithm based on heuristic rules with adaptive thresholds and ranges to segment the gait cycle of both legs.
3) **Data Storage Unit** - comprises an OTG USB driver to store the inertial data and the gait events identified.
4) **Mobile App** - Android App that connects to the processing unit wirelessly (via Bluetooth) in order to start/stop data acquisition, manage the operability settings and plot the acquired data.

5) **+S Desktop GUI** - interface built in MATLAB® with the goal of estimating gait-associated metrics. Therefore, it allows to load the data collected, detect and correct the gait events to estimate the desired metrics.

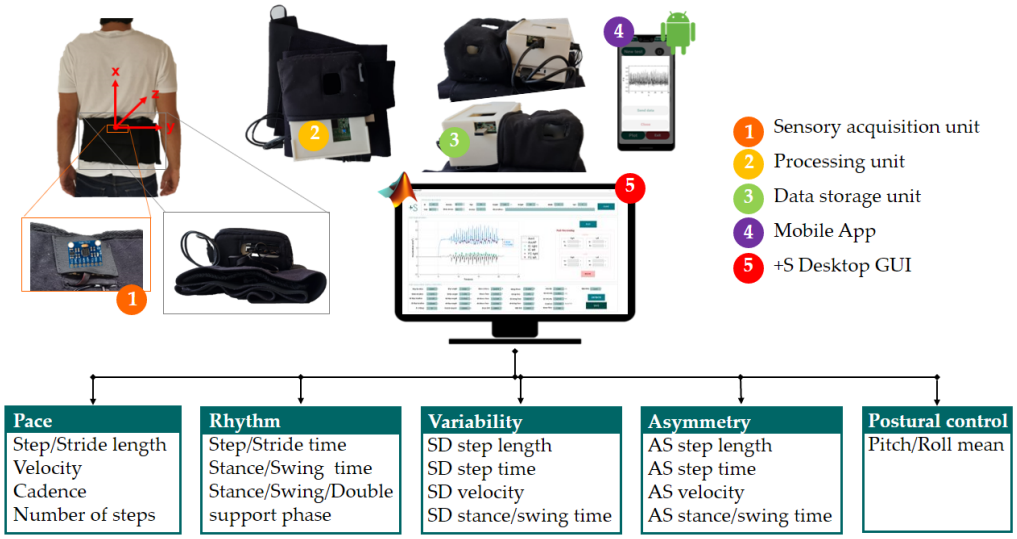

Figure 12: Overview of the HW and SW of the +sMotion module.

This dissertation addressed the **development of a new +S Desktop GUI (in Python using Kivy) which allows to analyse and estimate, not only gait-associated metrics, but also postural-related metrics from gait signals and other day-to-day activities** such as 90° and 180° turns, sitting, lying and getting up (from a bed or chair) and also the pull test, as presented in Figure 13.

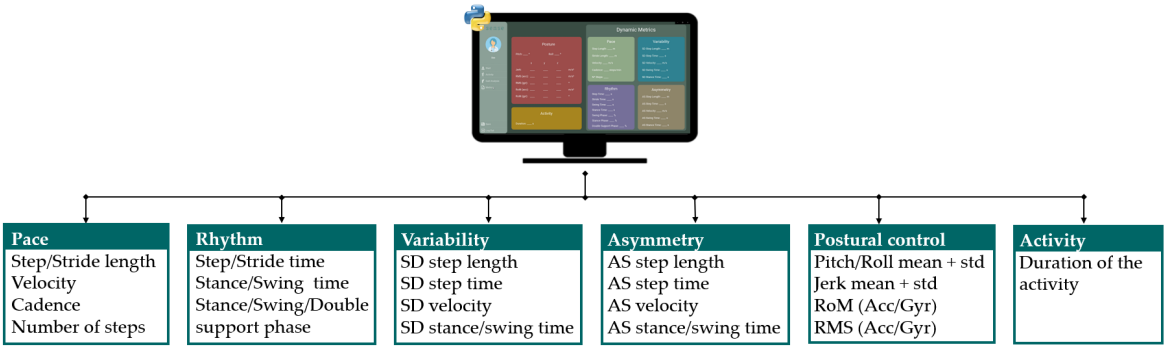

Figure 13: New +S Desktop GUI built in Python for the +sMotion module.

3.1.2 +sC-support

The +sC-support module applies AI-based algorithms to the outcomes of the +sMotion module seeking to correlate motor metrics with clinical scales in order to assess, for example, the disease progression, motor status and quality of life levels. Through a user-friendly application, this module works as a complementary diagnosis tool that clinicians can use during their consultations, and it aims to help them better monitor the progression of the disease and provide more personalized treatments.

This dissertation contributed to this module with an **extensive statistical study to verify if it is possible to use gait and postural-related metrics of day-to-day activities to differentiate between the various groups of the pull test score**, the UPDRS-III score, the H&Y score and between healthy subjects and PD patients. Moreover, some **AI-based algorithms were applied to distinguish the different scores of the pull test** using as input data the metrics estimated or the raw signals acquired from the inertial measurement unit. The AI-based algorithm with the best results was integrated into the new +S Desktop GUI, being possible to classify the pull test score based on the acceleration and angular velocity signals acquired from the CoM while performing one of the tasks.

3.2 User-friendly APP for Diagnostic & Management of Motor Symptoms in PD

The developed APP aimed to serve as a tool capable of reading the DAT files with acceleration and angular velocity signals to accurately compute postural and gait metrics and classify postural instability through the pull test score using an AI-based algorithm.

As can be seen in Figure 15 in the lateral navigation bar, the APP contains four main windows to load, adjust and process the data: 'Start', 'Activity', 'Gait Analysis' and 'Metrics'. It is possible to view a video of the APP using the QR code in Figure 14.

Figure 14: QR code to view a demonstration of the APP.

3.2.1 Start

Once a user logs into the APP, the initial interface corresponds to the 'Start' window which is divided into four sections: 'Personal Info', 'Date', 'Load Data' and 'Report' as presented in Figure 15.

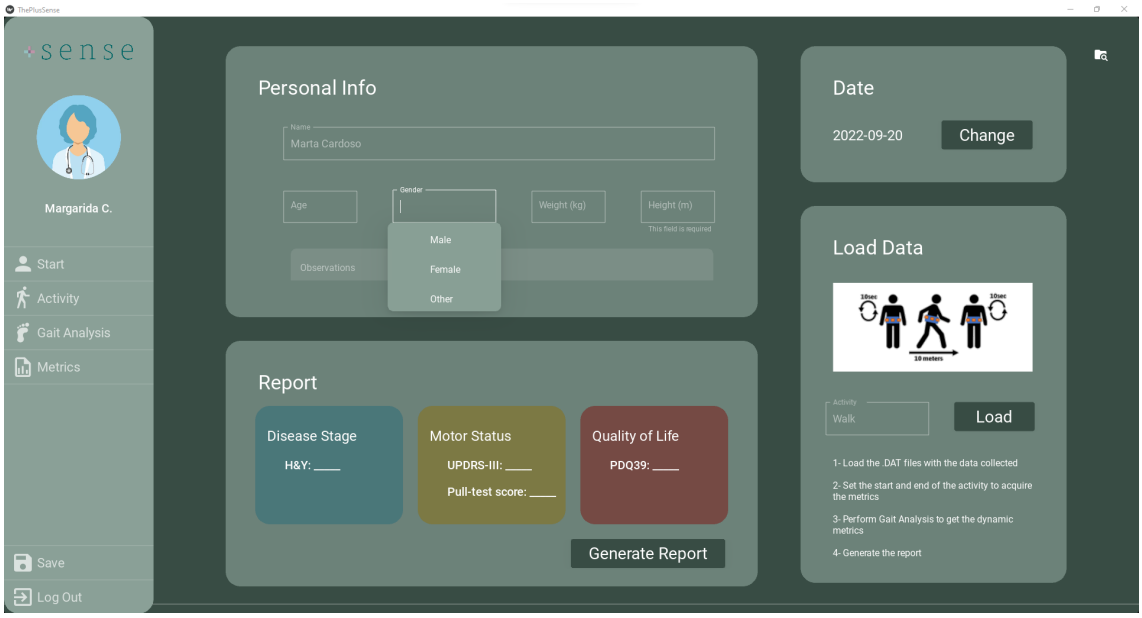

Figure 15: Window from the APP containing the personal information from the patient, to load the data and to estimate the pull test score.

In the 'Personal Info' section, the user can fill out the demographic data of the patient, which includes the name, age, gender, weight and height, and also some relevant observations. The only field required to fill for the activities that involve walking is the height of the patient as this value is used to estimate some of the gait metrics. In the 'Date' section, the user can set the day on which the trials were performed by clicking the button 'Change'. Regarding the 'Load Data' section, the user can choose the activity to load and load the respective DAT file by pressing the 'Load' button. For the activity selected, this section contains a figure with the steps to perform the task and instructions on how to proceed to acquire the metrics and generate the report. Before uploading the DAT file, it is possible to change the directory to load and save the files by clicking on the file symbol in the top left corner. Finally, the 'Report' section contains the scores of several clinical scales regarding the stage of the disease, motor status and quality of life which can be obtained using the 'Generate Report' button.

3.2.2 Activity

After loading a DAT file, it is necessary to select the start and end of the activity in the 'Activity' window, presented in Figure 16, for the metrics to be estimated only in that interval.

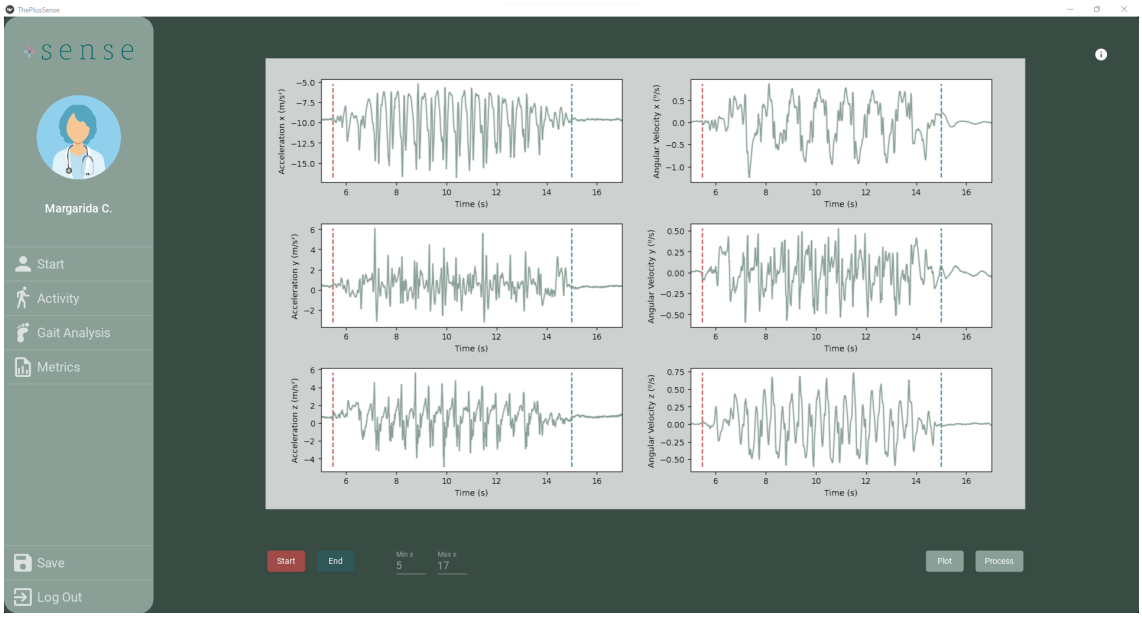

Figure 16: Window from the APP to identify the beginning and end of all activities.

The first step is to click the button 'Plot' to plot the six signals from the DAT file. After that, the beginning and end of the activity can be chosen by pressing the buttons start or end, respectively, and by selecting the time in one of the plots. Additionally, it is possible to zoom in/out the plots by setting the maximum and minimum values of the time axis. The last step consists in clicking the button 'Process' to estimate the metrics.

3.2.3 Gait Analysis

When the activity selected involves walking, it becomes necessary to identify, in the acceleration plots, the times of the initial contact (IC) and final contact (FC) of each leg in order to estimate the gait metrics. This can be done in the 'Gait Analysis' tab, presented in Figure 17.

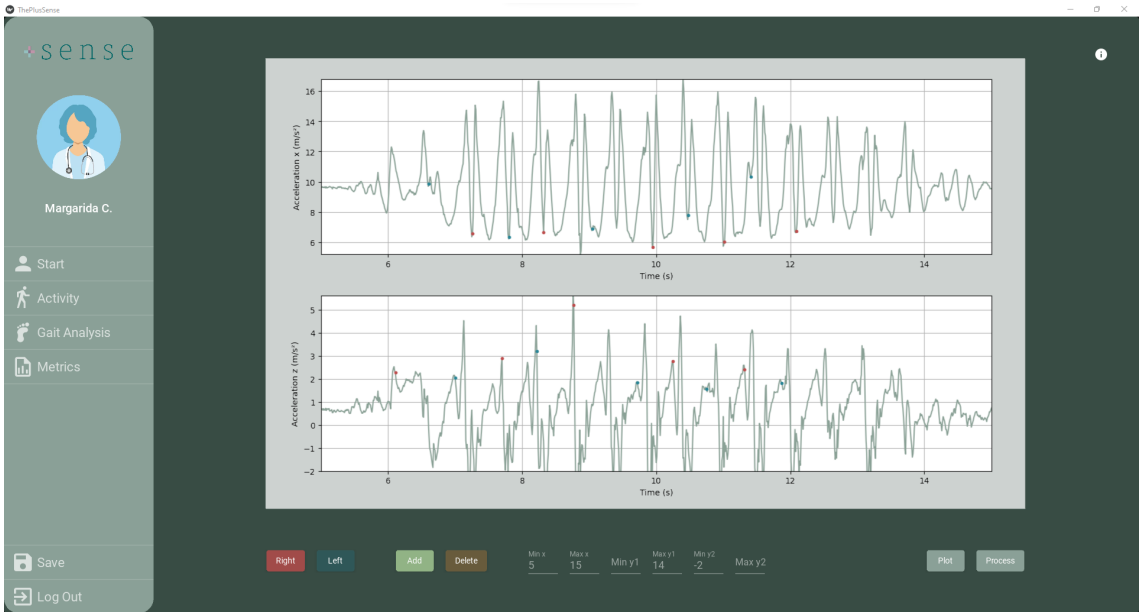

Figure 17: Window from the APP to identify the ICs and FCs of the activities that involve walking.

By pressing the 'Plot' button the acceleration signals appear in the window and, through a gait event detection algorithm, the times of the IC and FC are determined and appear in the plots as red/blue dots. The dots in the upper plot (acceleration in the x-axis – VT direction) correspond to the FC time values and the ones on the plot below (acceleration in the z-axis – AP direction) to the IC time values. As the gait event algorithm is not 100% accurate given the heterogeneity of walking of subjects with PD, some adjustments can be performed by selecting the 'Right'/'Left' and 'Add'/'Delete' buttons depending on the action to be executed. By selecting the 'Delete' button, any dot that was placed incorrectly can be excluded and by choosing the 'Add' button, a dot regarding the right or left leg can be added if the button selected is the 'Right' or 'Left', respectively. Once more, the plots can be zoomed in/out by specifying the maximum and minimum time/acceleration values. The gait metrics can be acquired using the 'Process' button.

Note that, the algorithm for the gait event detection was previously validated and described in [37], being based on heuristic rules with adaptive thresholds and ranges to detect foot initial and final contact from both legs (with a mean sensitivity of 99,53% and an accuracy of 97,42%).

3.2.4 Metrics

Once the previous steps are completed, it is possible to analyse the metrics estimated in the 'Metrics' tab, which can be observed in Figure 18.

Figure 18: Window from the APP to analyse the metrics estimated.

The features in the posture and activity sections are calculated for all the different tasks using the 'Process' button in the 'Activity' tab. The features included in the dynamic metrics section are only computed, in the 'Gait Analysis' tab by pressing the 'Process' button, if the task loaded involves walking. All features can be saved in an excel file using the 'Save' button in the bottom right corner of the window in the lateral navigation bar.

3.3 Data Acquisition

A number of public datasets were taken into consideration to train and evaluate the AI-based algorithms to differentiate the scores of the pull test. However, none of the datasets found, satisfied the goals of this dissertation as most of these did not include PD patients performing all sorts of day-to-day activities like turning, lying or sitting, or the data was not acquired with an inertial measurement unit on the lower back. Therefore, a new dataset was developed.

The data acquisition with pathological end-users was carried out in Hospital of Braga, with the collaboration of the physicians from 2CABraga, following the Helsinki Declaration and the Oviedo Convention, in accordance with the ethical guidelines of the Ethics Committee in Life and Health Sciences (CEICVS147/2021). All participants provided their informed consent to be part of the study.

3.3.1 Participants

Twenty-three patients with idiopathic PD (fourteen males and nine females) and ten healthy subjects (five males and five females) were recruited and accepted to participate in the data acquisition. The two groups do not have significant differences in terms of age, sex, height and weight as is possible to observe in Figure 19 and Table 7. Furthermore, Figure 19 presents the distribution of the patients regarding the stage of the disease (H&Y score), motor disability (UPDRS-III score) and postural instability (pull test score).

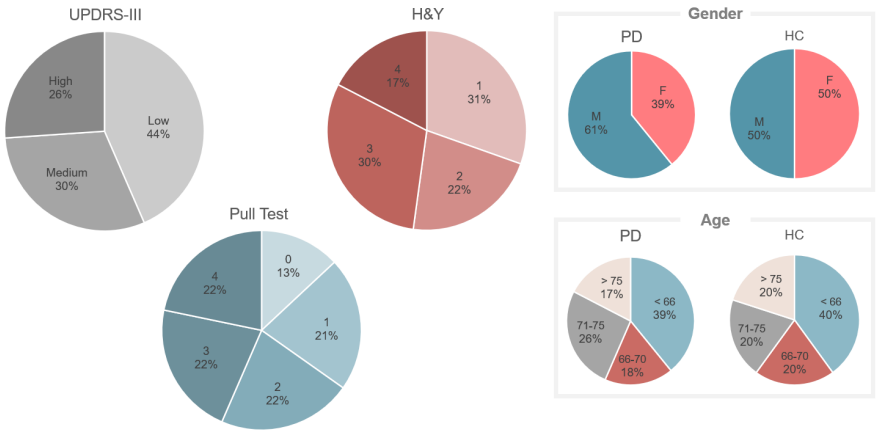

Figure 19: Distribution of the participants in terms of gender and age and of the PD patients in terms of the scores on the clinical rating scales.

A list of the inclusion and exclusion criteria was outlined in order to select the participants with PD for the experimental data collection. Participants were recruited if they: i) had between 45 and 80 years of age; ii) had a diagnosis of PD according to the UK PD Society Brain Bank criteria; and iii) were able to stand independently. On the other hand, subjects were excluded if they: i) presented any neurological disorder other than PD; ii) had any other condition that could affect their balance or gait. Table 7 presents the participants' detailed demographic and clinical data. Note that, patients participated while "on" antiparkinsonian medication.

Table 7: Participants demographic data and clinical rating scores.

Participant ID	Age (years)	Gender (M/F)	Weight (Kg)	Height (cm)	UPDRS-III score	H&Y score	Pull test score
P1	71	F	72	160	L	2	1

Continued on next page

Table 7 – *Continued from previous page*

Participant ID	Age (years)	Gender (M/F)	Weight (Kg)	Height (cm)	UPDRS-III score	H&Y score	Pull test score
P2	84	F	63	155	M	4	4
P3	76	M	74	175	L	1	2
P4	69	F	70	160	H	4	3
P5	70	F	72	160	M	3	3
P6	73	F	62	160	H	4	4
P7	75	M	75	165	M	3	3
P8	57	M	86	174	L	1	1
P9	76	M	75	172	L	1	2
P10	64	M	60	170	L	2	1
P11	70	M	61	170	L	1	0
P12	49	M	80	170	L	1	0
P13	75	M	65	175	M	3	1
P14	65	M	73	162	L	1	0
P15	61	F	62	169	M	2	2
P16	59	M	78	180	L	2	2
P17	79	F	40	150	H	4	4
P18	73	M	78	167	M	3	2
P19	56	M	66	168	L	1	1
P20	64	F	97	163	M	2	3
P21	55	M	75	166	H	3	3
P22	67	F	73	164	H	3	4
P23	72	M	63	164	H	3	4
H1	77	F	62	165	-	0	0
H2	71	F	63	167	-	0	0
H3	69	M	83,5	172	-	0	0
H4	76	F	58	164	-	0	0
H5	67	F	69	165	-	0	0
H6	65	F	68	167	-	0	0
H7	63	M	80	176	-	0	0
H8	73	M	74	168	-	0	0
H9	48	M	92	174	-	0	0

Continued on next page

Table 7 – *Continued from previous page*

Participant ID	Age (years)	Gender (M/F)	Weight (Kg)	Height (cm)	UPDRS-III score	H&Y score	Pull test score
H10	50	M	84	180	-	0	0
P mean ± std	67.83 (± 8.67)	-	70.43 (± 11.02)	166.04 (± 6.99)	-	-	-
H mean ± std	65.80 (± 9.92)	-	72.22 (± 11.26)	169.80 (± 5.41)	-	-	-

* The UPDRS-III score was divided in three categories: Low (L) if below 32, Medium (M) if between 32 and 64 and High (H) if above 64.

3.3.2 Materials

The setup for the data acquisition comprised:

- **Participants' demographic registration document**;
- **UPDRS-III and H&Y scales** to assess the participants' motor disability and the stage of the disease, respectively;
- **+sMotion (instrumented waistband)**, a single wearable device to collect inertial information regarding the CoM, at a frame rate of 100 Hz;
- **Xsens®** to be used as the ground-truth of the inertial data collected.

3.3.3 Data collection methods and study variables

In order to acquire the dataset, a protocol comprising the criteria for participant selection, the tasks for the data acquisition and the evaluation to be performed was delineated and is detailed in Appendix A.

The first step of the experimental procedure, as can be seen in Figure 20, was to get the participants' informed consent signatures and their demographic data (age, gender, weight and height). Before beginning the execution of the motor tasks to collect the inertial data, the participants with PD also had to undergo an evaluation to record the current stage of the disease (H&Y score) and their motor disability level (UPDRS-III score).

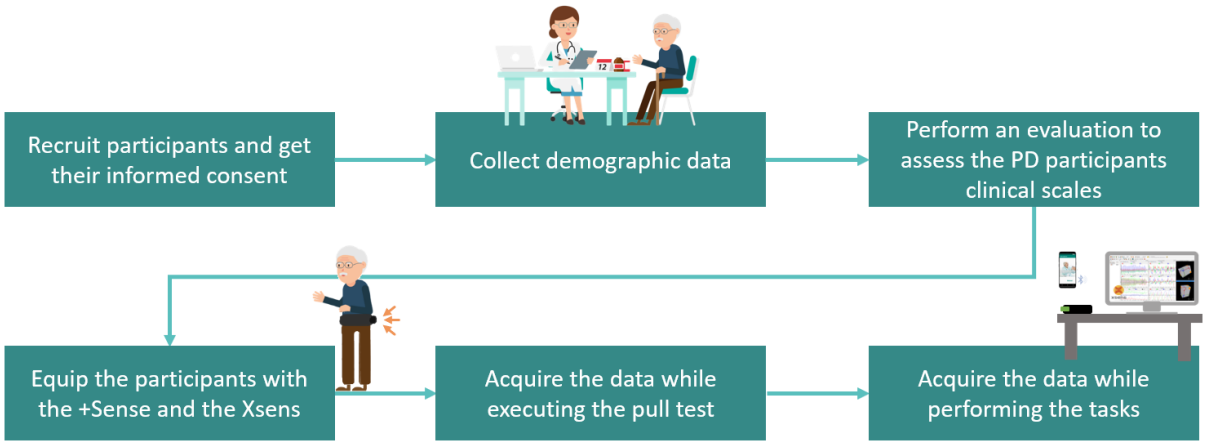

Figure 20: Diagram representing the steps for the data acquisition.

Afterwards, the participants were instructed to put on the +sMotion and Xsens equipment. Note that the IMUs of the two systems were placed in the lower back (L3-L5 level), near the CoM, and as close as possible to guarantee that the signals could be compared. To avoid a misalignment in the sensors outcomes, it was always the same person to place the sensors in participants.

The data acquisition started with the execution of the pull test. Subsequently, all participants followed the tasks described in the protocol, which involved sitting and getting up from a chair, lying and getting up from a bed, walking 10 meters in a straight line and performing 180° and 90° turns (both to the left and the right), as shown in Figure 21. Each task was explained and demonstrated before starting to collect the data and each one was executed three times for a higher statistical significance during movement evaluation.

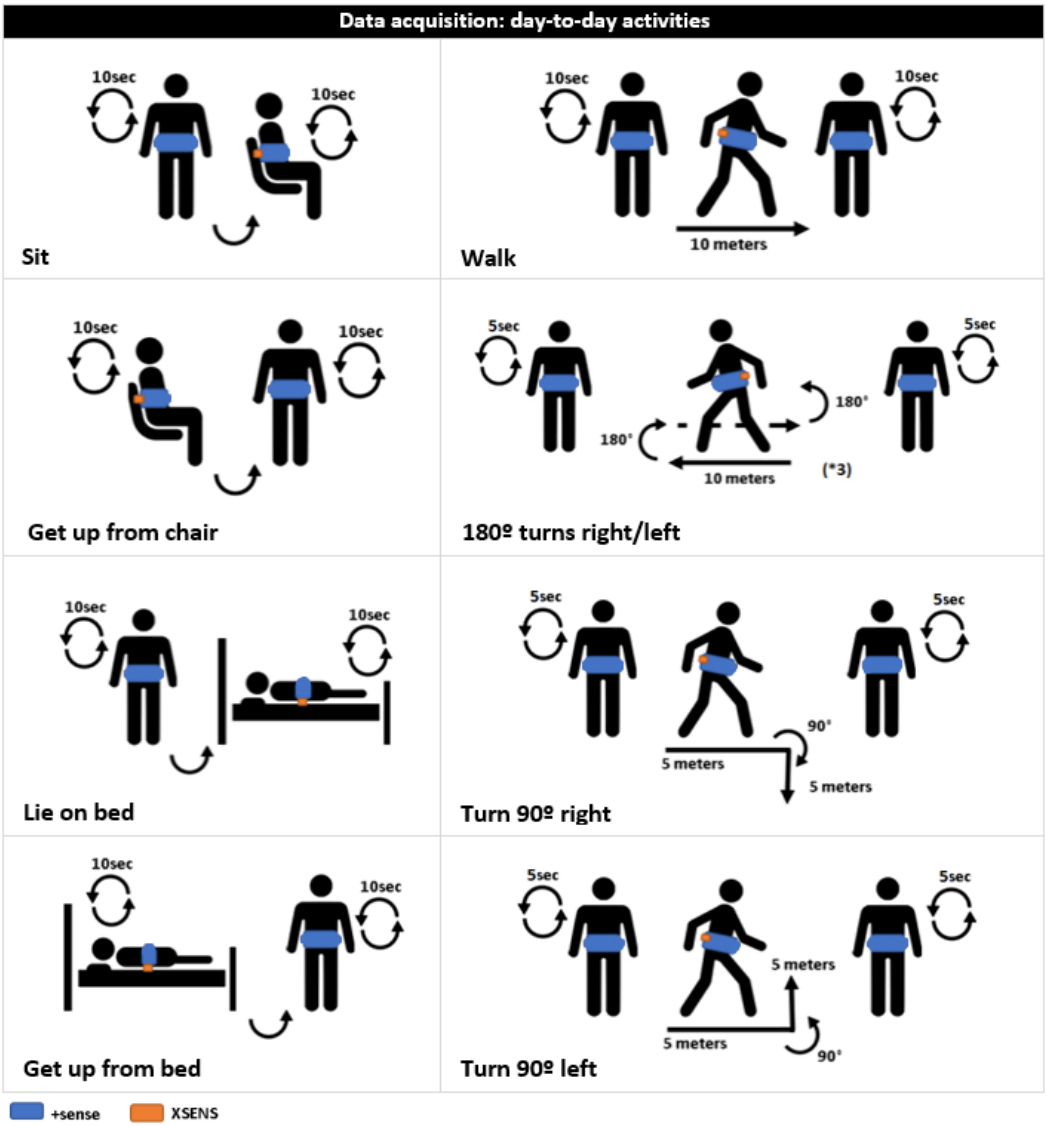

Figure 21: Tasks comprised in the experimental protocol for the data acquisition.

3.4 Data Analysis

Once the acquisition was completed, the inertial data collected from the Xsens was stored as text files and the data from the +sMotion as DAT files for a subsequent validation through Python. The raw signals of acceleration and angular velocity in the three axes (x, y and z) from the two systems were then overlaid. By observing the collected signals with both systems, it was possible to detect a mild difference in the mean value of the acceleration in z and y, which may be due to the positioning of the IMUs, as these could not be precisely placed in the exact same location. However, by removing the DC component, the signals

overlap, being possible to conclude that the signals acquired from the +sMotion are as accurate and valid as the Xsens. Further, this observation was supported by a previous benchmarking analysis of +sMotion with Xsens, where non-statistical differences were measured between both systems ($\rho \geq 0.19$) [37].

Once the eligibility of +sMotion data was validated, an APP was developed in Python to load and process the inertial data in order to estimate the desired postural and gait metrics. Through the metrics acquired, a statistical analysis was carried out to find if the features extracted from basic daily activities can distinguish between the different levels of postural instability. Subsequently, another script was developed to implement AI-based algorithms to predict the pull test score from the raw signals acquired while performing the activities. The best model created was then included in the APP.

4

STATISTICAL-BASED APPROACH TO SUPPORT POSTURAL ASSESSMENT

Recent studies demonstrated that IMUs are an affordable and portable solution to assess postural sway, which provides features sensitive to balance disorders. However, based on the information collected, no study tried to correlate the features acquired to the pull test score and no study was performed on (near) home-based conditions or even included features from functional tasks more similar to the daily context. Hence, this research focused on investigating if it is possible to differentiate between all the scores of the pull test through postural and gait metrics extracted from raw acceleration and angular velocity signals from the CoM acquired while performing basic day-to-day tasks.

This chapter comprises a description of the features extracted from the inertial data collected during the execution of the tasks present in the protocol described in the previous chapter and how these are expected to behave with the pull test score. This is followed by a brief explanation of the statistical analysis that was performed using SPSS, the results and subsequent analysis of the findings.

4.1 Data Analysis

As stated before, the Python environment was used to extract several features of the acceleration and angular velocity signals. The features extracted for each trial were chosen and studied based on the related state-of-the-art presented in Chapter 2 and consisted in:

- **Duration of the activity** - it is expected for this feature to increase with the pull test score as postural instability affects the execution of even the most basic tasks.

- **Jerk** (mean and standard deviation) - the first-time derivate of the acceleration; represents the relative smoothness of postural sway so, while for standing, patients with a higher score on the pull test may present a higher variation of jerk (an increased standard deviation) due to frequent postural corrections, for dynamic activities the expected is the opposite as the LOS decreases with postural instability which leads to a more cautious behaviour to perform the exercises.
- **RMS** (of the acceleration and angular velocity) - this value relates to the vibration levels of a signal, so once more, especially on the angular velocity signals, the RMS may decrease as the pull test score gets higher.
- **RoM** (of the acceleration and angular velocity) - keeping the same line of thought, the range of the signals is also expected to diminish as the pull test score increases.
- **Pitch and Roll** (mean and standard deviation) - if the pitch (ML rotation) and roll (AP rotation) are acquired while standing, both values are expected to get higher with the pull test score due to frequent postural adjustments. However, during dynamic tasks, as postural instability leads to performing the tasks more carefully, the standard deviation values of the Roll should get lower as the pull test score increases in the activities that require more rotation of the trunk in the AP direction as lying on the bed or walking but, above all, turning. This value could also get higher in activities that do not involve as much trunk rotation in the AP direction as people with postural instability perform more corrections to keep balanced. In regard to the pitch, the standard deviation value is expected to increase in general with the pull test score for the same reason. This should be noticeable especially during the execution of the pull test as people with higher postural instability get destabilized more easily and are not able to recover as quickly or smoothly.

For the walking trials, the following gait metrics were estimated by previously performing gait segmentation to identify the initial contact (IC) that corresponds to the heel strike and the final contact (FC) or toe-off.

- **Step and Stride time/length** - as aforementioned, patients with higher postural instability tend to present a more cautious behaviour in performing the tasks, which leads to slower and smaller steps.
- **Velocity and cadence** - as the pull test score increases it is expected a lower velocity and consequently cadence.

- **Number of steps** - as the patients with higher pull test scores may present smaller steps, the number of steps needed to walk a certain distance gets bigger.
- **Stance, Swing and Double support time/phase** - with a reduced LOS, the swing time tends to decrease and the double support phase to increase.
- **Asymmetry (AS) and standard deviation (SD)** of step length/time, velocity and stance/swing time - it is expected for patients with decreased postural stability to have walking patterns less regular and with fluctuations, as well as steps not symmetric, therefore these values may increase with the pull test score.

Before estimating these values, it was necessary to pre-process the data. This is a crucial step as it allows to eliminate irrelevant information. The pre-processing included converting the acceleration signals to m/s^2 and normalizing them, for the values to be between -1 and 1. After that, the angular velocity signals were converted to rad/s and calibrated so the mean of the signal was 0 when the participant was standing still. Lastly, the beginning and end of the task execution were selected for the metrics to be estimated only on that interval.

Subsequently, a statistical analysis was performed using the SPSS software. The PD patients were split according to their score on the pull test and two healthy participants were also included so each of the five groups contained information regarding five participants. The next step involved acquiring the descriptive statistics to summarize the information of each of the groups and applying the Shapiro-Wilk test to find out which features followed a normal distribution with a significance (sig) level of 5%. A certain population was considered normally distributed if the sig value was higher than 0.05.

As most of the features did not present a normal distribution, the test chosen to determine which features are capable of distinguishing the groups of the different pull test scores was the Kruskal-Wallis. This is a non-parametric test, which means that it is not necessary for the population to have a certain distribution for these methods of statistical analysis to be performed. The results of this test are presented in Tables 9 to 17 in Appendix B, in which the difference of a certain feature between the several groups is considered significant if the sig value is smaller than 0.05. When a feature was considered suitable to distinguish between the groups, it was also performed multiple comparisons to determine which groups had significant

differences. The tables present the significant sig values of the Kruskal-Wallis test and of the multiple comparisons highlighted.

Furthermore, the Pearson product-moment correlation (with a 95% confidence interval for each correlation coefficient) was used to assess the correlation between the selected features and the pull test score. The closer this value is to one, in module, the stronger the linear correlation between the feature and the pull test score. The values of the Pearson product-moment correlation can be observed in Table 21 in Appendix B. If the correlation was considered strong, which means if it was above 0.4 in module, then the values appear highlighted on the table.

Finally, a multiple linear regression was performed for each of the different activities to verify if the features extracted could be used to predict the pull test score. The results given in Table 26 contain the variables that were included in each of the models, the adjusted R squared of the model and the sig value of the ANOVA. The R squared determines the ratio of variance in the pull test score that can be described by the features included in the model. The closer to one, the better the data fits the model. The sig value of the ANOVA reveals if the relationship between the pull test score and features included in the model is statistically significant. The correlation is considered significant if the sig value is smaller than 0.05.

The same approach was followed to investigate whether these features were also suitable to distinguish between patients with PD and healthy subjects, the scores of the H&Y and the scores of the UPDRS-III. The results of these studies are presented in Appendix B. Note that to differentiate between PD patients and healthy subjects the test used instead of the Kruskal-Wallis was the Mann Whitney as in this case it was only necessary to make a distinction between two groups.

4.2 Results

The Kruskal-Wallis test revealed that most of the features estimated (167 out of the 229) are able to differentiate between at least two groups of the pull test score, as presented in Tables 9 to 17. Despite that, none of the metrics acquired while performing the pull test were considered significant to distinguish between the distinct pull test scores. Five metrics were considered relevant in all motor tasks, with exception of the pull test, which were the duration of the activity and the RMS and RoM of the angular velocity in the AP and VT directions.

It is also important to note that only the task of getting up from a bed had metrics capable of differentiating between all the groups of the pull test score. The tasks that included sitting or getting up from a chair did not have features to discern between scores 2 and 3, and the tasks that involved walking and turning could not discriminate between the participants in the lower end of the pull test score. In specific, the data acquired while performing turns of 180º only provided metrics to discriminate between participants with no posture instability and the maximum score on the pull test.

The Kruskal-Wallis test also confirmed that many of the features can distinguish the healthy participants from the patients with PD as depicted in Table 18, the patients in different stages of the disease (H&Y score) as shown in Table 19, and the patients with distinct levels of motor disability (UPDRS-III score) as presented in Table 20. In all the cases, the activity considered less significant to distinguish between the groups was the pull test. Regarding the UPDRS-III score, all the activities were able to make a distinction between all of the levels, except for the tasks involving sitting and turning 180º which could not separate patients with medium and higher scores of motor disability. Besides that, almost all the activities could discern all the stages of the disease. The exceptions were the ones that consisted in sitting and lying, which could not differentiate between milder stages of the disease and the transition to a moderate stage, respectively, and turning 180º which could only separate between a milder and moderate stage of the disease.

By observation of Table 21 which contains the values of the Pearson product-moment correlation (with a 95% confidence interval for each correlation coefficient) between the selected features and the pull test score, it is possible to infer that, of all the features extracted, the ones that presented a higher correlation to the pull test score were the duration of the activity, the variation of roll in the tasks that included turning and the RMS and RoM of the angular velocity, especially in the AP direction.

It is noteworthy that the features mentioned above also present a high correlation to the stage of the disease, the level of motor disability and the diagnosis of the disease. Tables 23 and 24 demonstrate that the RMS of the acceleration in the AP and ML directions also correlate highly with the H&Y and UPDRS-III scores. As for distinguishing patients with PD from HC, other features that significantly correlated were the variation of jerk in the AP and ML directions, and the RoM of the acceleration, as can be seen in Table 22.

In regard to the gait-associated metrics, by observation of Table 25 it is possible to conclude that, the features with a higher correlation to the pull test score, the H&Y score, the UPDRS-III score and to distinguish

between PD patients and HC were all the same and consisted in the step/stride length, velocity and number of steps.

The multiple linear regression results, presented in Table 26, revealed that, with exception of the pull test and the task that consisted in getting up from a chair, it was possible to create a model for each activity that could explain at least 50% of the variability of the pull test score. The metrics most included in the models were RMS and RoM of the angular velocity and acceleration in the direction of movement of the task execution. Other relevant features were the duration of the activity for the tasks that involved turning and the mean jerk of the acceleration in the AP direction for tasks that involved lying or getting up from a bed.

Additionally, similar conclusions can be taken from the models created to predict the H&Y and the UPDRS-III scores. As for predicting if a participant is a PD patient or HC, relevant features in the models, besides RMS and RoM, were activity duration in the tasks involving sitting and getting up from a chair and the pull test, mean jerk of the acceleration in the VT direction for tasks that involved lying or getting up from a bed, and pitch mean for activities including 90° turns.

4.3 Discussion

The key finding in this study was that the features extracted from the acceleration and angular velocity signals from the CoM while performing day-to-day tasks can distinguish between all of the pull test scores. In fact, the results presented previously indicate that IMU-based technology may be a useful mean to monitor the progression of postural instability in PD patients in day-to-day settings.

Based on the information acquired, no other study has been made under these conditions or to the end of discriminating between all the scores of the pull test. Most of the studies found on this subject involved using IMUs to analyse postural instability during quiet stance in different conditions (altered surface, stance and/or vision) or during weight-shifting exercises with the goal of extracting metrics capable of differentiating patients with PD from HC [9, 12, 16, 21, 24–27, 29, 30]. There was even a study that, through IMUs placed on the feet, attempted to analyse gait to detect postural instability and provide a separation of HC and two PD groups (with and without postural instability) [19]. One of the studies had an acquisition protocol including the dynamic activities comprised on the TUG test, however, the data collection was made with more IMUs in different locations of the body, and it only attempted to correlate the features extracted with the level of motor disability [18].

Through the statistical analysis of the features extracted, it was possible to conclude that all the day-to-day activities performed during the data collection include metrics relevant to distinguish between at least two groups of the pull test score. This result was expected as postural instability compromises the execution of even the simplest daily tasks. Interestingly, the pull test was the only task from which no metrics extracted were able to separate between any of the 5 groups. Furthermore, as PD patients present other motor symptoms that progress over time and with the stage of the disease which also affect basic dynamic activities, all the tasks, with exception of the pull test, provided significant features to differentiate patients with PD from HC, the several stages of the disease and the levels of motor disability (scores of the UPDRS-III).

The Pearson product-moment correlation between the selected features and the pull test score revealed that the hypotheses aforementioned regarding how the features evolve with the pull test score were verified. In fact, as patients with higher postural instability exhibit decreased LOS, magnitude of postural responses and postural reflexes, they tend to perform the tasks more carefully. While performing dynamic tasks, this behaviour leads to slower execution of the activities, smaller variation of jerk, decreased RMS and RoM of the angular velocity, decreased RoM of the acceleration in the direction of movement during the task execution (which was mostly in the AP and VT direction) and also a smaller variation of the roll especially in the tasks that involved turning.

Regarding the gait-associated metrics, the result once more was the expected, and it is possible to conclude that, during the execution of activities that involved walking, the participants with higher postural instability display slower and smaller steps, which lead to an increased number of steps and decreased cadence. Moreover, the time in the double support phase increases and the walking pattern gets less regular and with less symmetric steps.

The metrics that presented a higher correlation to the pull test score were the duration of the activity, the variation of roll in the tasks that included turning, the RMS and RoM of the angular velocity, especially in the AP direction, step/stride length, velocity and number of steps. Curiously, all these metrics also highly correlated to the stage of the disease, the level of motor disability and the diagnosis of the disease.

With respect to the multiple linear regression models created, the activities that could better predict the pull test score were lying or getting up from a bed, walking and turning 90°. The variables with most impact in all these models were the RoM and RMS of the acceleration and angular velocity signals in the direction

of movement of the execution of the task, emphasizing once more that postural instability leads to a more cautious behaviour, leading to slower movements and with less magnitude/lower range.

5

AI-BASED APPROACH TO SUPPORT POSTURAL ASSESSMENT

Deep learning has become well-known in the areas of speech and image classification, however, its' potential to analyse wearable sensor data has not yet been completely investigated. Therefore, the goal of this research was to explore deep learning as an approach for IMU-based postural instability evaluation.

This chapter describes the three deep learning frameworks employed to classify the postural stability level of PD patients through the raw acceleration and angular velocity signals from the CoM acquired while performing basic day-to-day tasks or through features extracted from these signals. Therefore, the chapter starts by summarizing how the datasets are prepared and the training pipeline, followed by the results, discussion and conclusions taken from the AI-based algorithms created.

5.1 Dataset Preparation

The data acquired during the trials consisted of the acceleration and angular velocity (on each of the three axes – x, y, z) of the CoM of the subject while performing several day-to-day activities, as presented in Chapter 3. Each acquisition corresponded to a single activity of a participant and the inertial data was stored in DAT files.

In order to prepare the data to be used in the AI-based algorithms for postural assessment, two python scripts were developed (one for the raw signals of acceleration and angular velocity and another for the features extracted of these signals). The first script, mentioned in the previous chapter, was used to extract features from the raw signals, which were then stored in a csv file with the corresponding label of the pull test score. Regarding the second script, the first step consisted in converting each DAT file to csv format.

Subsequently, a label with the pull test score was added to each csv file and the signals were shortened so their length was a multiple of the timestep in which the signal was going to be analysed.

Afterwards, before splitting the data from both scripts into different datasets (training, validation and testing), all the activities were shuffled for the datasets to be representative of the whole distribution. Finally, the data was split to create 4 datasets as presented in Figure 22, in which:

- **Training dataset to find the best hyperparameters**: 80% of the data was selected to perform a **grid search** for the best hyperparameters;
- **Training dataset**: 80% of the first training dataset was selected to **train** the model with the best hyperparameters;
- **Validation dataset**: The remaining 20% of the first training dataset was selected for **validation** in the final training phase;
- **Testing dataset**: The 20% remaining of all the data was selected to **test** the model;

The percentage chosen to split the data was based on prior similar studies [38, 39].

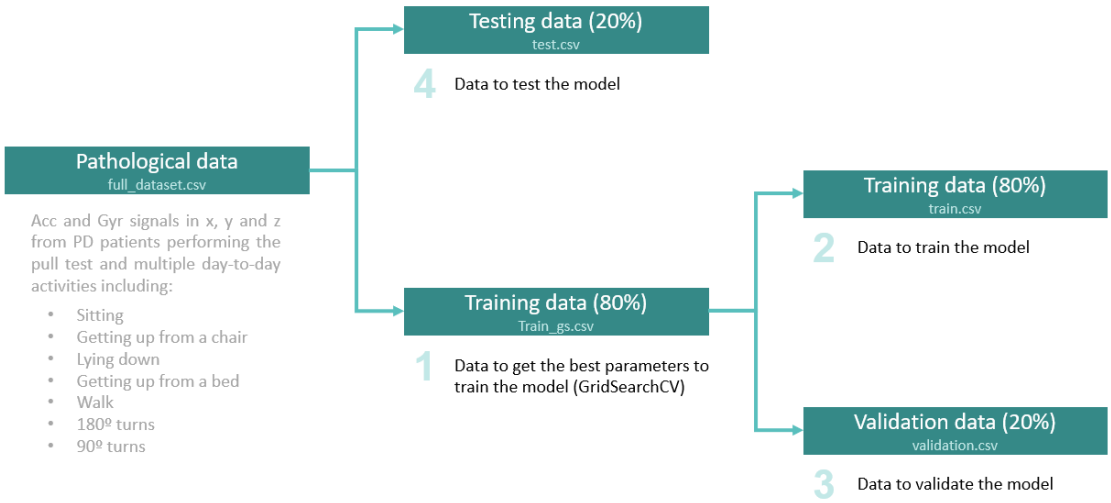

Figure 22: Diagram representing how the data was split into the four datasets.

5.2 Training Pipeline

After preparing the datasets, a script in python using Keras and TensorFlow was developed to implement the neural network algorithms for postural assessment.

As can be observed in Figure 23, the process starts with loading the csv files with the four datasets and pre-processing the data, which, in the case of using the raw signals as input data, consisted in dividing the signals of acceleration and angular velocity of each task in non-overlapping segments of 2.4 seconds and normalizing their values. The size of the window was based on a previous study regarding human activity recognition using deep learning [40]. The size of the window has to be adjusted to the study as small window sizes may not include enough data to capture a pattern, while large window sizes lead to a longer training process and could contain patterns too sophisticated. Note that, for using the features extracted from the signals as input data, the prepossessing consisted solely in normalizing the values.

Subsequently, a grid search was performed for hyperparameter optimization. The range of possible hyperparameters was manually specified and based on previous studies [38, 39]. The search for the best hyperparameters included a cross-validation technique, k-fold cross-validation, with 10 folds, meaning that, for every combination of hyperparameters, the data was divided into 10 parts and the training of the model was executed 10 times always leaving 1 different subset of the data out for it to be used to validate the model. The average performance of the 10 models was then estimated. The set of hyperparameters was chosen based on the F1-score as this is a measure commonly used for class imbalance (classes that do not contain an equal number of instances).

Once the grid search was completed the model was trained using the training dataset and the best hyperparameters, and the metrics were estimated with the validation dataset. The model was then saved, and a final set of metrics was estimated using the test dataset.

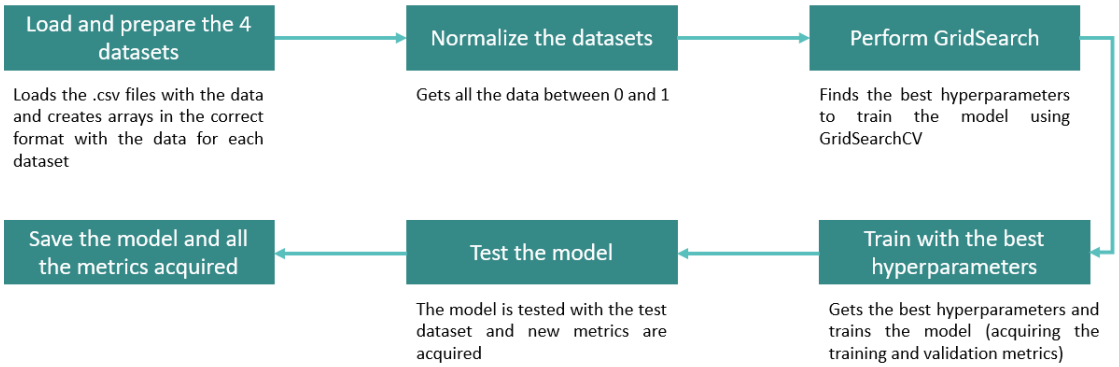

Figure 23: Diagram representing the steps implemented in the neural network algorithms.

The deep learning algorithms chosen to classify postural instability in PD patients based on the raw signals of acceleration and angular velocity were the convolutional neural networks (CNN) and long short-term memory networks (LSTM). The CNN are known for creating feature maps to learn from the given data which significantly improves the classification accuracy and the LSTM is a well-known deep learning model adequate for processing time series and multi-classification problems.

The CNN deep learning framework employed two convolutional neural network layers with rectified linear units (ReLUs), a dropout layer, one max-pooling layer, a layer to flatten the data into a single dimension instead of two, and two fully connected layers (one with ReLUs and another with a softmax for classification). The architecture described is presented in Figure 24.

In the convolutional layers a kernel is convolved with the inputs to generate a tensor of outputs which is then transformed using ReLUs. Several convolutional layers can be stacked for features with higher levels of abstraction to be learned from the data. With the output from the convolutional layers a random dropout and the max pooling operation are applied in order to reduce the overfitting of the network. The dropout mechanism randomly drops a certain percentage of units of the layer and the max pooling process extracts the maximum value of patches of the output from the previous layer, generating a down-sampled feature map. This feature map is then flattened, and the first fully connected layer attempts to acquire features suitable for the classification step. The last fully connected layer uses the softmax activation function to determine the probability of each class. The number of neurons in the output layers corresponds to the number of classes that can be predicted, in this case, 5. The output neuron with the highest value (probability) corresponds to the class predicted.

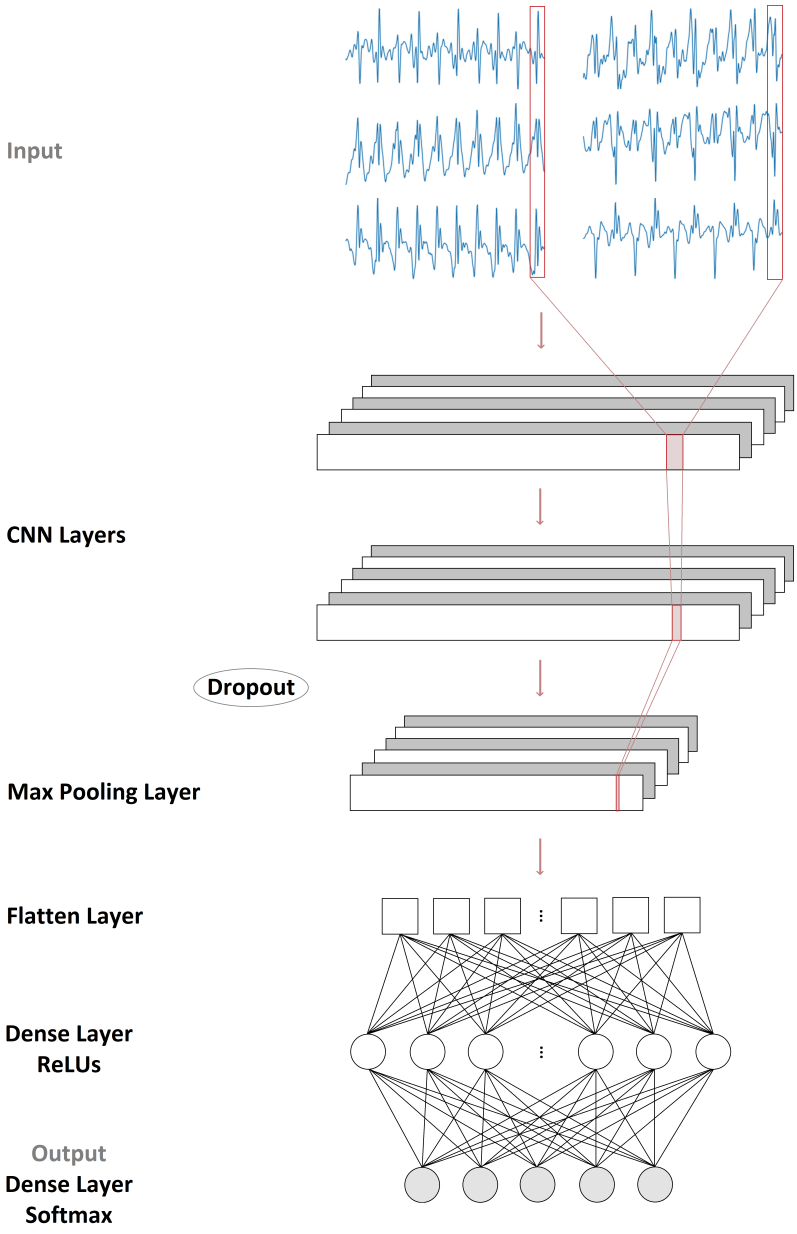

Figure 24: Architecture of the CNN deep learning framework.

The LSTM deep learning framework presented an input layer with batch normalization, three bidirectional LSTM layers with dropout, a layer to flatten the data into a single dimension instead of two, a dropout layer and two fully connected layers (one with ReLUs and another with a softmax for classification). The architecture described is presented in Figure 25.

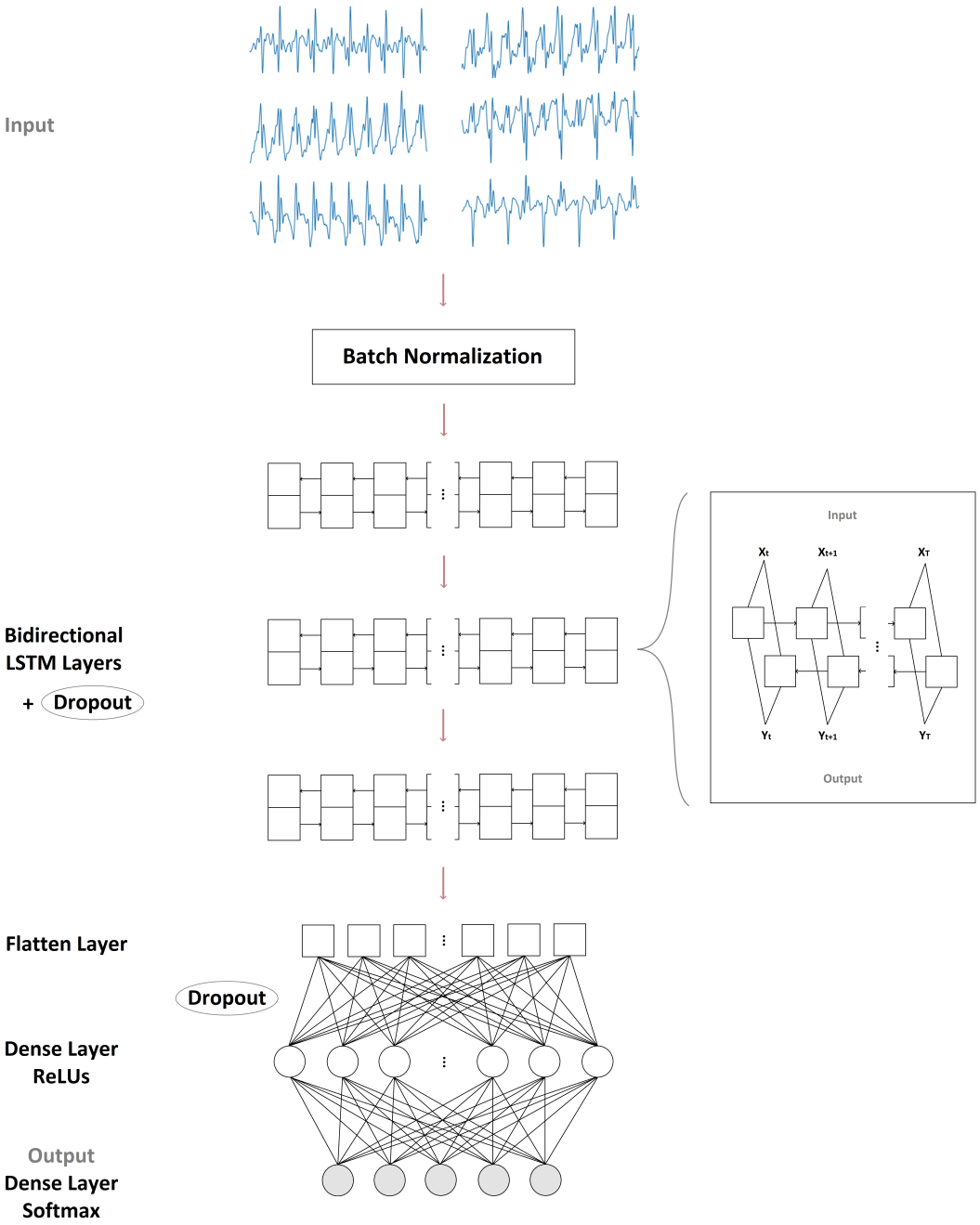

Figure 25: Architecture of the LSTM deep learning framework.

In the batch normalization layer, the batches of input data are standardized and normalized for the neural networks to be more stable and faster by decreasing the number of epochs needed for the training. The subsequent LSTM layers contain a specific gate structure in order to 'remember' crucial information and 'forget' unnecessary information learned previously. Additionally, by continuously backpropagating useful

information, these layers are capable of learning long-term dependencies. The bidirectional LSMT is the combination of two LSTM, which allows to analyse both past and future events by having a LSTM moving forward on the data and another one moving backwards. After the final LSTM layer, the outputs are converted to a single dimension in the flatten layer and go through a process of random dropout to reduce overfitting. Finally, the fully connected layers learn to recognize features to perform the classification.

To enhance this study, based on the promising results from the statistical analysis of the metrics estimated, and to continue evaluating the importance of the deep learning models, the multilayer perceptron networks (MLP) were chosen to classify postural instability in PD patients based on the metrics estimated with the +sMotion APP as there was no need for this model to be as deep as the others since it was not necessary to analyse time series to extract features.

The MLP deep learning framework employed two dropout layers and three fully connected layers (two with ReLUs and another with a softmax for classification). The architecture described is presented in Figure 26.

The neurons in the first two dense layers identify characteristics from the input data suitable for the classification step. In turn, the output layer determines the probability of each class using the softmax activation function.

As stated before, to find the best hyperparameters to train the model, a range of values was manually set for each of the three algorithms. The first hyperparameter specified was the batch size for the data to be fed to the network in batches to speed up the learning process. However, larger batch sizes may lead to an under-generalized model not capable of fitting new data well. After that, it was defined the number of neurons in the hidden fully connected layers and also the number of epochs, which consists of the number of times the data is going to be presented to the network during the training. The number of neurons in these layers and the number of epochs should not be too high or too low since that could result in overfitting (learning so much from the data that the model is not able to generalize) or underfitting (not learning properly), respectively. Another hyperparameter established was the learning rate which reflects how quickly the weights of the network are going to be updated. Higher learning rates speed up the process but may cause divergent behaviour in the loss function, whereas small learning rates require more epochs as the updates to the weights are smaller. Regarding the convolutional layers, the hyperparameters configured were the number of filters applied and the size of the kernel. As for the max polling layer, it was the poll

size. Finally, for the dropout layers, it was the dropout rate in order to avoid overfitting. This value has to be adjusted as higher values can result in under-learning and lower values may have a minimal effect.

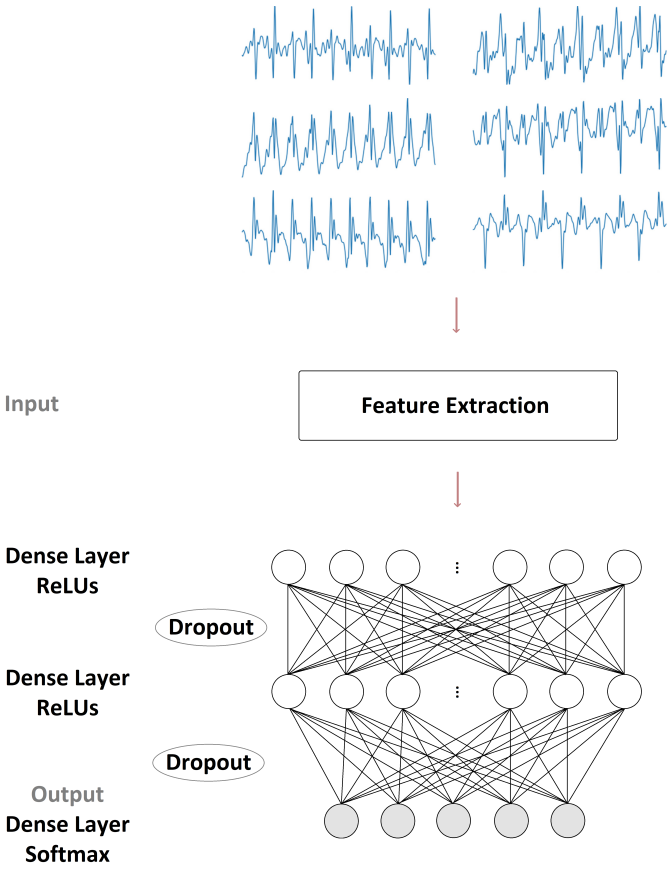

Figure 26: Architecture of the MLP deep learning framework.

5.3 Metrics Evaluation

In order to assess the efficacy of the classifiers, several performance metrics were estimated:

- **Accuracy**: one of the most common measures and can be described as the ratio between the correct predictions of the model and the total number of predictions;
- **Recall**: it is a mean of how good the model is to predict each of the scores of the pull test and can be defined as the proportion of the number of times one class was correctly classified and the number of times the class should have been predicted;
- **Precision**: it is a mean of how many of the predictions are correct for each of the scores of the pull test and can be defined as the fraction of the number of times one class was correctly classified and the number of times the class was predicted;
- **F1-score**: harmonic mean of the recall and precision, in order to combine these two metrics into one;
- **AUC**: it is the area under the receiver operating characteristics (ROC) curve; this metric shows how well the model can distinguish between the different scores of the pull test and correctly classify each one of the classes;
- **Loss**: score that compares the predicted probability of each class with the expected output; the higher the value the more the predicted probability diverges from the desired output.

5.4 Results

Table 8 summarizes the performance metrics acquired for the models using different datasets and types of neural networks, and Figure 27 presents the confusion matrix for the model of each dataset that presented the best results when tested with previously unseen data.

Table 8: Performance metrics of the best models of each dataset and NN type.

Dataset	NN Type	Epochs	Hyperparameters		Step	Loss	Accuracy	Precision	Recall	F1	AUC
All	CNN	300	Batch size	64	Train	0.3804	0.8454	0.8884	0.8028	0.8430	0.9810
			Filter	64							
			Kernel size	6	Validation	1.2105	0.5934	0.6582	0.5125	0.5747	0.8713
			Pool size	3							
			Neurons	60							
			Dropout rate	0.5	Test	1.0139	0.7001	0.7470	0.6078	0.6679	0.9045
			Learn rate	0.001							
All	LSTM	183	Batch size	64	Train	0.1043	0.9627	0.9676	0.9569	0.9621	0.9984
			Filter	-							
			Kernel size	-	Validation	3.5087	0.6173	0.6228	0.6008	0.6115	0.8156
			Pool size	-							
			Neurons	60							
			Dropout rate	0.3	Test	2.8517	0.6122	0.6168	0.6037	0.6101	0.8362
			Learn rate	0.001							

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Table 8 – *Continued from previous page*

Dataset	NN Type	Epochs	Hyperparameters		Step	Loss	Accuracy	Precision	Recall	F1	AUC
All except Pull Test	Conv1D	292	Batch size Filter Kernel size Pool size Neurons Dropout rate Learn rate	64 32 6 3 100 0.3 0.001	Train	0.3746	0.8502	0.8918	0.8089	0.8479	0.9818
					Validation	1.1955	0.6981	0.7486	0.6091	0.6693	0.8879
					Test	1.3561	0.6261	0.6390	0.5462	0.5881	0.8660
All except Pull Test	LSTM	200	Batch size Filter Kernel size Pool size Neurons Dropout rate Learn rate	64 - - - 60 0.3 0.001	Train	0.1252	0.9528	0.9558	0.9453	0.9504	0.9969
					Validation	2.8974	0.6132	0.6288	0.6078	0.6180	0.8285
					Test	3.0723	0.5918	0.5887	0.5737	0.5810	0.8208
Walking Activities	CNN	142	Batch size Filter Kernel size Pool size Neurons Dropout rate Learn rate	64 64 6 3 100 0.3 0.001	Train	0.1475	0.9407	0.9487	0.9349	0.9417	0.9971
					Validation	0.5534	0.8357	0.8693	0.8049	0.8355	0.9626
					Test	0.7119	0.8076	0.8341	0.8078	0.8206	0.9465

Continued on next page

Table 8 – *Continued from previous page*

Dataset	NN Type	Epochs	Hyperparameters		Step	Loss	Accuracy	Precision	Recall	F1	AUC
Walking Activities	LSTM	74	Batch size	64	Train	0.0763	0.9696	0.9681	0.9656	0.9669	0.9989
			Filter	-							
			Kernel size	-	Validation	0.3239	0.9130	0.9163	0.9104	0.9134	0.9819
			Pool size	-							
			Neurons	60							
			Dropout rate	0.3	Test	0.5552	0.8625	0.8599	0.8599	0.8599	0.9696
			Learn rate	0.001							
Metrics	MLP	386	Batch size	256	Train	0.1451	0.9555	0.9552	0.9434	0.9492	0.9959
			Filter	-							
			Kernel size	-	Validation	0.7606	0.8571	0.8571	0.8571	0.8571	0.9491
			Pool size	-							
			Neurons	100							
			Dropout rate	0.2	Test	2.1934	0.7810	0.7789	0.7714	0.7751	0.9318
			Learn rate	0.01							

By analysing the performance of the models using as a dataset the raw acceleration and angular velocity signals of all the activities while tested with unseen data, it can be concluded that the best results were obtained with the CNN algorithm. The accuracy, precision, recall and F1-score were all between 60% and 75%. The metric with the lowest value was the recall and the metric with the highest percentage was the precision. This indicates that there are more false negatives (FN) than false positives (FP), which means that on average, for a certain class, it is more likely to get a prediction wrong when the level of postural instability in question corresponds to that class, than to predict that a person with another level of postural instability corresponds to that class. Note that the performance metrics acquired from the training were significantly higher which may imply overfitting, the model being too adapted to the training data.

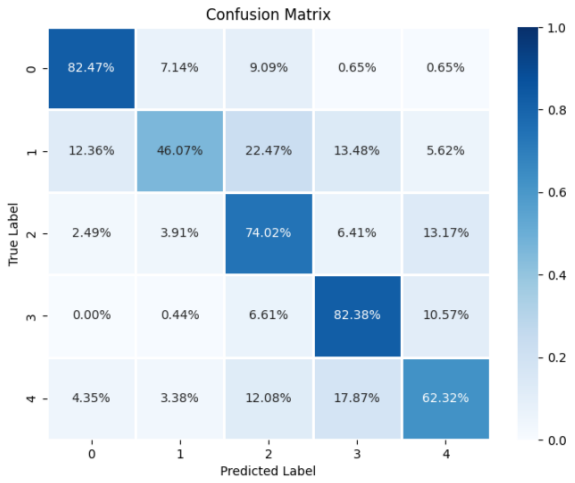
In an attempt to improve the performance of the model, two other datasets were created with fewer activities included:

- **All except the pull test**: this dataset comprised only the day-to-day activities;
- **Walking activities**: this dataset included all the activities that involved walking (walking 10m, turning 90º and 180º).

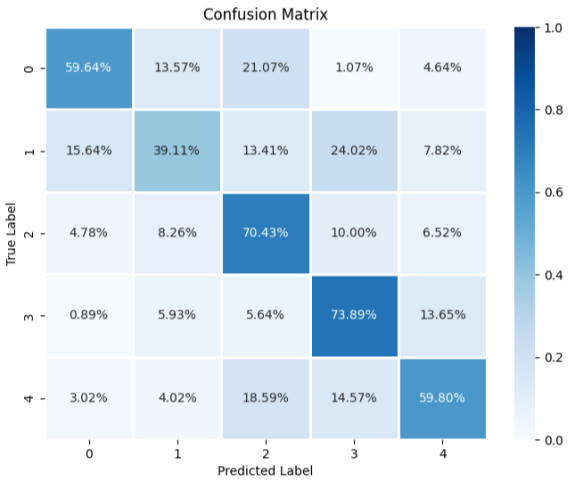
By observation of Table 8, it is possible to verify that the models created with the dataset containing only day-to-day activities (all except the pull test) got worse metrics when tested with unseen data. However, these models showed better results in the training and validation which implies higher overfitting of the data, not being able to fit new data as well.

Regarding the models using as a dataset the activities that involved walking, the performance metrics while testing with new data, with the training data and with the validation data were significantly better than the best model using as a dataset all the activities. In this case, the best results were achieved with the LSTM algorithm in which the values of accuracy, precision, recall and F1-score of the test were approximately 0.86.

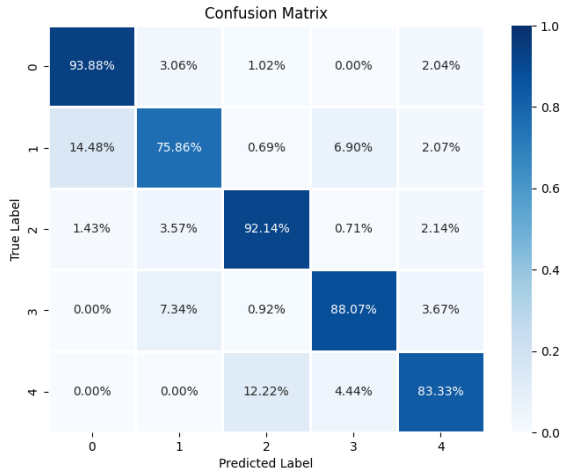
Finally, as aforementioned, there was also a model created using as a dataset the metrics extracted from the signals of acceleration and angular velocity with +sMotion APP. This model was able to get better metrics in the training, validation and testing steps than the best model using as dataset all activities, but worse in comparison to the best model using as dataset the walking activities.



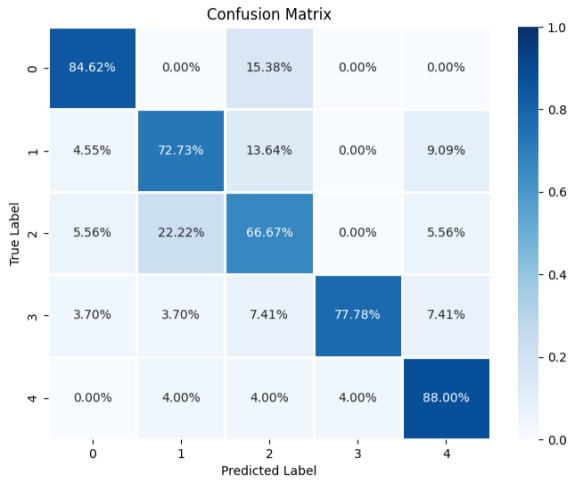
(a) Confusion Matrix of the model with the CNN algorithm and using the dataset that includes all activities.



(b) Confusion Matrix of the model with the CNN algorithm and using the dataset that includes all activities except the pull test.



(c) Confusion Matrix of the model with the LSTM algorithm and using the dataset that includes all activities that involve walking.



(d) Confusion Matrix of the model with the MLP algorithm and using as dataset metrics extracted from the inertial data.

Figure 27: Confusion Matrix for the best model created with each dataset

Observing the confusion matrixes presented in Figure 27, it is possible to perceive that especially when using the dataset with all the activities or only the ones that involve walking, people with a pull test score of 0 are more easily identifiable than people who present postural instability. People with a pull test score of 1 may get mixed up with someone with no postural instability when their gait is being evaluated, but also with

people with even more postural complications when all the activities are analysed. Moreover, to confirm the results stated before, the model created with the walking dataset was the model capable of getting more correct predictions in all the different scores of the pull test, with exception of a pull test score of 4 in which it was possible to get more predictions correct with the model using as dataset the features extracted from the inertial data collected.

5.5 Discussion

The purpose of this research was to investigate the use of deep learning as an approach to assess the level of postural instability through raw data collected from a wearable IMU located in the CoM of a user while performing basic daily tasks. Even though the research had some limitations, the results presented suggest that deep learning may be promising in the area of IMU-based postural instability assessment.

Deep learning has already been used for PD diagnosis or to detect certain motor symptoms, but based on the information collected, it has not been applied to the field of postural instability analysis. There is a study that uses deep learning to predict if PD patients present bradykinesia from inertial data collected with IMUs on the wrist while performing movement exercises with the upper limbs [41]. Another study implemented a deep learning algorithm to distinguish between people with PD from HC by extracting gait metrics from data acquired with an IMU on the CoM while walking [39]. In contrast to these last two studies, which only perform a binary classification, the models presented in this research execute multi-category classification. One of the studies found also predicted more than two classes, the aim was to classify the severity of the disease through the data gathered from force sensors on the feet while walking [38].

The major advantages of deep learning consist in (i) not needing to rely on features determined by experts, neural networks are able to extract very meaningful features; (ii) similarly to an expert evaluation, it allows to analyse the signal segment of a task as one, providing a single output; (iii) with new data becoming available, the framework can be improved and be able to generalize to new data better, producing better results. Note that, for this last step to improve the model, it is necessary that the data collected is labelled by clinical experts.

Based on the results presented in the previous section, it is possible to infer that the model that achieved the best performance metrics was the LSTM algorithm with the walking activities as a dataset. Hence, the network benefited from having less variability of activities. As can be observed in Table 8, when the dataset

includes all the different tasks, the models end up overfitting, not being able to generalize as well, and, as a result, may not be suitable in wider clinical and scientific settings. This may be happening due to the high number of features being introduced in the model in comparison to the number of subjects participating in the research. Therefore, reducing the number of different activities to train the model reduces the complexity of the model, making it more efficient.

The confusion matrixes confirmed that the model best suited to predict basically any of the pull test scores was the LSTM algorithm using as dataset only activities that involved walking. The confusion matrix also revealed that the scores with more correct predictions were the 0 and 2. In contrast, the scores with less correct predictions were the 1 and 4. People with a pull test score of 1 could be mistaken for someone with no postural instability, as for people with the highest level of postural instability, some were mixed up with people with a score of 2.

The limitations of this research included (i) the execution of the trials in a clinical setting instead of an actual home-like environment; (ii) the limited number of participants; and (iii) given the subjectivity of the pull test, the labels might not be completely accurate. In regard to the second limitation, additional data is required to increase the performance of the classification as deep learning relies deeply on the database. However, the results from this research support the argument for a more in-depth analysis of deep learning-based postural instability assessment through inertial data.

6

CONCLUSIONS AND FUTURE DIRECTIONS

Postural instability and gait disabilities are amongst the most incapacitating features of PD and threaten the independence and quality of life of PD patients. Regarding the first research question (**RQ1** - How is postural instability usually assessed?), the clinical examination used to assess postural instability is the pull test. This test is widely used since it is easy to administer and does not require specific instruments, however, it is a difficult test to standardize and therefore subjective and lacks sensitivity to detect small but significant changes. Additionally, it is essential for physicians to quantify gait and balance deficits and to perceive motor changes that lead to postural complications in order to monitor patients over time and implement an adequate treatment to improve postural stability and reduce the risk of falls. Hence, wearable sensors emerged as promising solutions to better capture postural instability and eliminate the subjectivity of postural-associated clinical examinations.

The state-of-the-art in wearable technology to assess postural responses and provide additional sensory information in order to improve postural control allowed to address the second research question (**RQ2** - Is there a more objective way to assess postural instability?) and revealed that there is a lack of investigation on assessing postural instability in dynamic conditions like while executing basic daily tasks. Most of the studies found on this subject focused on acquiring postural sway metrics through IMUs during quiet stance in different conditions (altered surface, stance and/or vision) with the goal of differentiating patients with PD from HC. Therefore, the main goal of this dissertation consisted in the design, development and validation of a postural assessment tool to make a more objective evaluation of postural instability under dynamic conditions.

This work addressed the development of a desktop APP to analyse raw inertial signals from basic daily activities to estimate gait and postural-related features and to predict the pull test score through an AI-based algorithm.

Through the application, the gait and postural-related features of all the data collected during the trials were estimated and an extensive statistical study was performed to answer the third research question (**RQ3** - Can metrics extracted from inertial data of daily activities be correlated to the pull test score? And to the UPDRS-III score, the H&Yscore or for diagnosis purposes?) by verifying if it is possible to use these features to distinguish between the different groups of the pull test score, the UPDRS-III score, the H&Y score and between healthy subjects and PD patients. The results revealed to be promising as, through the features acquired, it was possible to differentiate all the scores of the pull test, of the H&Y, of the UPDRS-III and between PD patients and healthy subjects. This indicates that inertial-based technology may be a useful mean to monitor the progression of postural instability in PD patients in day-to-day settings. The results also uncovered that, of all the exercises performed during the data acquisition, the pull test was considered less significant to distinguish between any of the groups and emphasised that postural instability leads to a more cautious behaviour even while executing basic daily tasks, leading to slower movements and with less magnitude/lower range.

Furthermore, in order to determine the AI-based algorithm to classify the pull test score of PD patients and answer the fourth research question (**RQ4** - Can deep learning be used to classify pull test score through inertial data of daily activities to increase the objectivity of postural instability assessment?), three deep learning frameworks were employed (CNN, LSTM and MLP) and four datasets were created (one including all the activities comprised in the protocol, another excluding only the pull test, one only with the tasks that involved walking and the last using the features estimated with the application). The results showed that the model that achieved the best performance metrics was the LSTM algorithm with the walking activities as a dataset. This implies that the network benefited from having fewer types of activities as it reduces the complexity of the model. In the cases in which the dataset included more activities, the model was not able to generalize as well to new data and ended up overfitting.

All of the goals set for this dissertation were achieved, however, future work should address the following points: (i) include a larger population to increase the performance of the classification of the deep learning model; (ii) enhance the quality of the acquired data by executing the trials on an actual home-like environ-

ment instead of in a clinical setting; (iii) develop and validate a biofeedback strategy to make PD patients aware of the required postural adjustments in real-time for a more effective motor rehabilitation.

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Part I

APPENDICES

A

EXPERIMENTAL PROTOCOL

Experimental Protocol

Postural Assessment in Parkinson's Disease

Purpose:

OB1: Create an open-source multimodal dataset of the pull test and physical activities in Parkinson's Disease based on 3D motion data and kinematic-driven gait parameters acquisitions through wearable miniaturized inertial sensors.
OB2: Assess dynamic postural instability.
OB3: Automatic estimation of pull test score based on artificial intelligence models.

Study design:

- Cross-sectional study.

Local:

- Hospital of Braga – 2CA Braga Academic Clinical Center.

Study chronology:

- **T0:** Patients' selection and recruitment
- **T1:** Experimental procedure
- **T2:** Data analysis
- **T3:** Dissemination

Figure 1 - Study chronology (W: week).

Participants:

- **Number of participants**: 15 participants with PD + 10 healthy controls

Table 1 - Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
• Diagnosis of PD according to the UK Parkinson's Disease Society Brain Bank criteria • Hoen & Yahr scale ≤ 4 • Age between 45-85 years old • Can stand independently	• Co-morbid disorders likely to affect gait, including stroke, rheumatologic disease and musculoskeletal disorders • Cognitive impairment • Obvious motor impairments • Cognitive impairments • Visual acuity deficits • Audiometric deficits • Other neurological disease • Pain that may affect walking

Material:

- Hoehn & Yar scale (H&Y)
- Unified Parkinson's Disease Rating Scale (UPDRS-III)
- Pull test score
- Participants demographic registration document
- +Sense waistband: +senseMotion
- Xsens:
    - 1 sensor: back lower trunk (L3-L5 level) of the participant
    - MTManager SW

Data acquisition and outcomes:

Table 2 - Acquired variables and respective necessary material

Type	Variables	Material
Clinic	Disease stage	H&Y
	Motor disability	UPDRS-III
Demographic	Age [years]	Participants demographic registration document
	Gender [F/M/Non-binary]	
	Weight [Kg]	
	Height [cm]	
Motion	1. 3D motion data 2. Kinematic-driven gait parameters: • Rhythm: step/stride time and stance/swing/double-support phase. • Pace: step/stride length, velocity, and cadence. • Variability: step length/time, velocity, and stance/swing phase standard deviation. • Asymmetry: step length/time, velocity, and stance/swing phase asymmetry. 3. Postural related metrics: • Trunk pitch and roll. • Range of motion. • Root mean square • JERK.	+senseMotion Xsens

Experimental procedure:

Step 1. Get participants' informed consent signature.
Step 2. Record participants' demographic data.
Step 3. Assess and record the participants' clinical scales (UPDRS-III except point 3.12).
Step 4. Put the Xsens on the participant.
Step 5. Put the +Sense on the participant.
Step 6. Turn on +Sense and pair with +S APP (table 3).
Step 7. Explain the first task (point 3.12 of UPDRS-III – pull test) to perform on data discrete type acquisition (table 4 and figure 2) and, if necessary, demonstrate it.

Step 8. In +S APP configure +sense to execute a motion monitoring acquisition as described in table 3.

Step 9. Connect +sense with Xsens base station via wire.

Step 10. Start data acquisition:

- **a.** Press start button in +S APP (table 3).
- **b.** Confirm in the Xsens desktop that the data acquisition has started and disconnect +sense to Xsens base station.
- **c.** Instruct the participant to start the explained task.
- **d.** Record the time the participants start a new activity transition.

Step 11. Finish data acquisition:

- **a.** Instruct the participant to finish the first motion trial.
- **b.** Press stop button in +S APP (table 3).
- **c.** Confirm in Xsens desktop if stopped data acquisition.

Step 12. Repeat the procedure from **step 8** until subsequently complete the tasks indicated on table 4 referred to data acquisition discrete type.

Step 13. In +S APP, plot acquired data to confirm that no losses have occurred during trials acquisition (table 3).

Step 14. Exit +S APP, turn off the +sense and remove it from the participant (table 3).

Estimated time per subject: ~30min

Table 3 - +S APP configuration for respective experimental step and +sense strategy

+S APP configuration	Experimental procedure	+sense command
	Step 7	Bluetooth pairing
	Step 9	Motion monitoring

+S APP configuration	Experimental procedure	+sense command
	Step 11	Start trial
	Step 12	Stop trial
	Step 14	Plot acquired data
	Step 15	Exit +SAPP

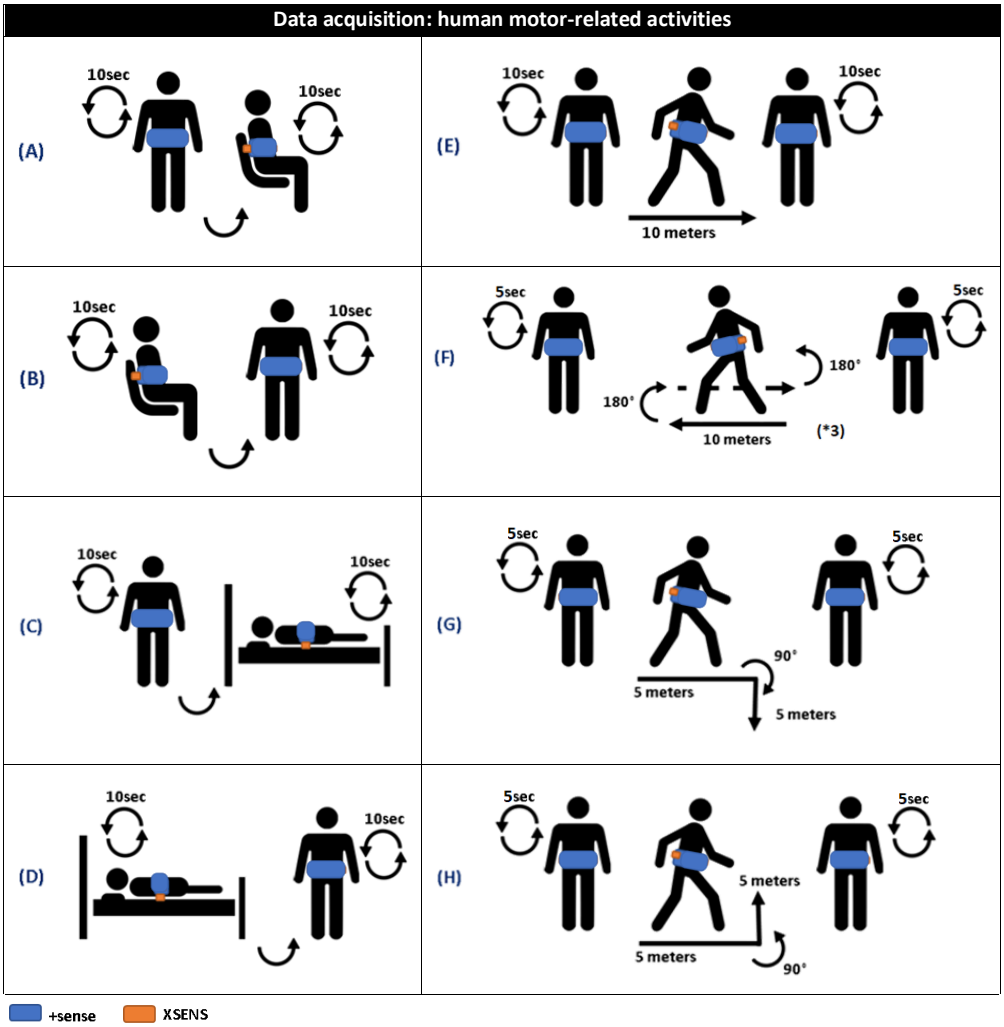

Figure 2 - Experimental procedure tasks for human motor-related activities: (A) Sit in a chair, (B) Get up from a char, (C) Lie on a bed, (D) Get up from a bed, (E) Walk/Stand, (F) Right/Left 90° turning, (G) Right 180° turning, (H) Left 180° turning.

Table 4 - Data acquisition type (discrete and continuous), physical activity and corresponding tasks, and estimated and total estimate time

Activity		Tasks	Estimated time	
			Per trial	Total
Pull-test (3.12 point of UPDRS-III)			15s	~1min
Human motor-related activities	(1) Sit in a chair	10s standing + sit in a chair + 10s sitting	25s	~12min
	(2) Get up from a chair	10s sitting + get up + 10s standing	25s	
	(3) Sit in a chair	10s standing + sit in a chair + 10s sitting	25s	
	(4) Get up from a chair	10s sitting + get up + 10s standing	25s	
	(5) Sit in a chair	10s standing + sit in a chair + 10s sitting	25s	
	(6) Get up from a chair	10s sitting + get up + 10s standing	25s	
	(7) Lie on a bed	10s standing + lie on a bed + 10s lying	25s	
	(8) Get up from a bed	10s lying + get up + 10s standing	25s	
	(9) Lie on a bed	10s standing + lie on a bed + 10s lying	25s	
	(10) Get up from a bed	10s lying + get up + 10s standing	25s	
	(11) Lie on a bed	10s standing + lie on a bed + 10s lying	25s	
	(12) Get up from a bed	10s lying + get up + 10s standing	25s	
	(13) Walk	10s standing + 10m walk + 10s standing	10s	
	(14) Walk	10s standing + 10m walk + 10s standing	10s	
	(15) Walk	10s standing + 10m walk + 10s standing	10s	
	(16) 180° turning	5s standing + (10m walk + right 180° turn + 10m walk + left 180° turn) * 3 + 10m walk + 5s standing	75s	
	(17) Right 90° turning	5s standing + 5m walk + 90° turn + 5m walk + 5s standing	25s	
	(18) Left 90° turning	5s standing + 5m walk + 90° turn + 5m walk + 5s standing	25s	
	(19) Right 90° turning	5s standing + 5m walk + 90° turn + 5m walk + 5s standing	25s	
	(20) Left 90° turning	5s standing + 5m walk + 90° turn + 5m walk + 5s standing	25s	
	(21) Right 90° turning	5s standing + 5m walk + 90° turn + 5m walk + 5s standing	25s	
	(22) Left 90° turning	5s standing + 5m walk + 90° turn + 5m walk + 5s standing	25s	

Data analysis:

Table 5 - Variables and methods designation to achieve respective study purposes

Purpose	Variables	Method
Create an open-source multimodal dataset of physical activities in Parkinson's Disease based on 3D motion data and kinematic-driven gait parameters acquisitions through on wearable miniaturized inertial sensors.	Motion data	Open-source database guidelines (https://www.dbta.com/Editorial/Trends-and-Applications/A-Practical-Guide-to-Adopting-an-Open-Source-Database-for-Enterprise-IT-Use-66368.aspx) OB1
Assess posture instability and estimate the pull test score using the created dataset.		AI-based models and statistical analysis OB2/3
Descriptive and visual analysis of clinical and demographic data.	Clinical and demographic data	Statistical descriptive (mean ± standard deviation) *

*SPSS will be used to accomplish the statistical analysis.

Schedule:

Tasks	Week											
	1	2	3	4	5	6	7	8	9	10	11	12
Recruitment	■											
Experimental procedures		■	■	■	■	■	■	■	■			
Data analysis					■	■	■	■	■	■	■	
Dissemination								■	■	■	■	■

B

TABLES STATISTICAL ANALYSIS

B.1 Descriptive Statistics, Normality Test and Test to Compare Between Independent Groups

B.1.1 Pull test score

Table 9: Descriptive statistics and results of the Kruskal-Wallis test for the pull test.

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Duration of the activity	**0**	3.656	1.042	0.439				
	1	2.784	0.796					
	2	3.324	0.658					
	3	2.978	1.155					
	4	3.452	1.309					
Jerk mean Acc x	**0**	-5.19E-04	3.66E-04	0.203				
	1	-4.32E-04	6.93E-04					
	2	-2.02E-04	4.57E-04					
	3	3.30E-04	8.53E-04					
	4	1.10E-03	2.15E-03					
Jerk mean Acc y	**0**	2.23E-04	4.88E-04	0.407				
	1	-5.29E-04	7.34E-04					
	2	-6.55E-04	1.55E-03					
	3	5.08E-04	1.65E-03					
	4	-1.64E-03	3.38E-03					

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Table 9 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Jerk mean Acc z	**0**	1.34E-03	1.41E-03	0.839				
	1	1.10E-03	2.61E-03					
	2	8.87E-04	2.34E-03					
	3	1.85E-03	6.37E-03					
	4	6.67E-03	1.15E-02					
Jerk std Acc x	**0**	0.743	0.552	0.609				
	1	0.555	0.372					
	2	0.477	0.242					
	3	0.840	0.749					
	4	0.989	0.578					
Jerk std Acc y	**0**	1.084	0.805	0.685				
	1	0.638	0.474					
	2	0.435	0.211					
	3	0.856	0.681					
	4	1.015	1.017					
Jerk std Acc z	**0**	1.080	0.862	0.881				
	1	0.968	0.937					
	2	0.528	0.369					
	3	1.351	1.813					
	4	1.294	1.307					
RMS Acc x	**0**	9.604	0.102	0.363				
	1	9.568	0.185					
	2	9.576	0.286					
	3	9.353	0.435					
	4	9.043	1.015					
RMS Acc y	**0**	1.595	0.795	0.193				
	1	1.330	0.803					
	2	1.094	0.430					
	3	2.161	0.444					
	4	1.817	0.928					
RMS Acc z	**0**	3.123	1.806	0.647				
	1	2.860	1.684					
	2	3.216	1.341					
	3	3.935	2.470					
	4	4.753	2.747					

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Table 9 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RMS Gyr x	**0**	22.086	12.226	0.236				
	1	9.724	10.152					
	2	5.661	7.493					
	3	12.506	20.632					
	4	3.225	6.444					
RMS Gyr y	**0**	18.628	5.545	0.649				
	1	12.298	12.149					
	2	10.137	13.615					
	3	23.668	40.846					
	4	5.226	10.271					
RMS Gyr z	**0**	9.747	3.915	0.165				
	1	4.305	5.048					
	2	2.642	3.519					
	3	6.048	9.991					
	4	1.452	2.835					
RoM Acc x	**0**	11.753	5.697	0.644				
	1	7.716	4.365					
	2	9.483	4.703					
	3	10.713	7.323					
	4	12.803	6.175					
RoM Acc y	**0**	14.871	8.143	0.613				
	1	9.619	7.930					
	2	7.117	3.428					
	3	11.457	5.985					
	4	16.828	20.026					
RoM Acc z	**0**	16.880	10.231	0.840				
	1	13.000	9.167					
	2	11.326	7.351					
	3	17.533	20.665					
	4	17.369	13.824					
RoM Gyr x	**0**	190.098	148.684	0.175				
	1	54.395	61.814					
	2	32.773	43.176					
	3	93.161	166.625					
	4	23.030	45.320					

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Table 9 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RoM Gyr y	**0**	138.718	60.012	0.486				
	1	86.689	90.141					
	2	78.352	113.587					
	3	170.344	320.469					
	4	36.550	69.422					
RoM Gyr z	**0**	67.966	17.675	0.136				
	1	31.962	37.952					
	2	19.456	25.760					
	3	39.038	67.231					
	4	10.954	21.244					
Pitch mean	**0**	-3.617	3.087	0.178				
	1	-0.988	3.104					
	2	-3.125	5.184					
	3	-0.197	6.579					
	4	-9.535	8.108					
Pitch std	**0**	4.318	0.973	0.339				
	1	5.448	1.846					
	2	6.235	3.296					
	3	6.409	5.653					
	4	10.790	7.361					
Roll mean	**0**	-0.208	1.607	0.193				
	1	0.140	0.441					
	2	1.021	1.469					
	3	0.958	1.230					
	4	-0.253	1.547					
Roll std	**0**	1.881	0.842	0.329				
	1	1.095	0.376					
	2	1.364	0.218					
	3	1.841	0.856					
	4	1.384	0.642					

Table 10: Descriptive statistics and results of the Kruskal-Wallis test for the task involving sitting.

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Duration of the activity	**0**	3.315	1.114	0.002	1.000	0.033	0.019	0.062
	1	3.396	0.638			0.264	0.170	0.435
	2	4.376	1.093				1.000	1.000
	3	5.375	2.626					1.000
	4	4.244	0.958					
Jerk mean Acc x	**0**	3.00E-04	1.14E-03	0.002	1.000	1.000	1.000	0.021
	1	-7.24E-05	2.93E-04			0.480	1.000	0.001
	2	6.38E-04	1.06E-03				1.000	0.629
	3	1.81E-04	1.50E-03					0.182
	4	1.53E-03	1.26E-03					
Jerk mean Acc y	**0**	1.09E-04	1.68E-03	0.003	0.237	1.000	0.174	0.030
	1	-8.38E-04	9.81E-04			0.222	1.000	1.000
	2	1.30E-04	9.84E-04				0.162	0.028
	3	-9.26E-04	1.01E-03					1.000
	4	-1.16E-03	1.21E-03					
Jerk mean Acc z	**0**	6.27E-03	3.60E-03	0.020	0.444	1.000	0.606	1.000
	1	3.41E-03	2.59E-03			1.000	1.000	0.051
	2	5.09E-03	4.84E-03				1.000	1.000
	3	3.54E-03	3.63E-03					0.077
	4	7.97E-03	4.39E-03					
Jerk std Acc x	**0**	0.224	0.074	0.023	1.000	1.000	0.348	1.000
	1	0.208	0.128			0.288	0.016	1.000
	2	0.277	0.117				1.000	1.000
	3	0.315	0.097					0.785
	4	0.264	0.156					
Jerk std Acc y	**0**	0.174	0.055	0.004	1.000	1.000	0.237	1.000
	1	0.180	0.224			0.327	0.002	1.000
	2	0.197	0.083				1.000	1.000
	3	0.248	0.085					0.135
	4	0.167	0.080					
Jerk std Acc z	**0**	0.253	0.094	0.011	0.050	1.000	1.000	1.000
	1	0.207	0.236			0.462	0.007	0.561
	2	0.238	0.108				1.000	1.000
	3	0.267	0.071					1.000
	4	0.230	0.117					

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Table 10 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RMS Acc x	**0**	9.471	0.091	0.009	1.000	1.000	0.018	1.000
	1	9.420	0.314			1.000	0.016	1.000
	2	9.293	0.361				0.744	1.000
	3	9.182	0.239					0.972
	4	9.359	0.178					
RMS Acc y	**0**	0.837	0.320	0.025	1.000	1.000	0.629	1.000
	1	0.777	0.548			1.000	0.060	0.418
	2	0.738	0.232				0.120	0.717
	3	1.126	0.382					1.000
	4	0.996	0.329					
RMS Acc z	**0**	2.532	1.018	0.013	1.000	0.641	1.000	0.111
	1	2.230	0.564			0.212	0.730	0.028
	2	3.264	1.366				1.000	1.000
	3	3.372	1.800					1.000
	4	3.494	1.087					
RMS Gyr x	**0**	6.832	3.865	0.023	0.393	0.016	0.551	0.096
	1	3.446	3.916			1.000	1.000	1.000
	2	2.496	3.391				1.000	1.000
	3	6.290	9.097					1.000
	4	2.397	4.744					
RMS Gyr y	**0**	24.216	7.986	0.002	0.166	0.041	0.004	0.004
	1	12.623	10.629			1.000	1.000	1.000
	2	8.257	10.114				1.000	1.000
	3	9.312	12.188					1.000
	4	6.055	11.999					
RMS Gyr z	**0**	4.948	1.862	0.010	0.814	0.006	0.190	0.106
	1	2.901	2.523			0.875	1.000	1.000
	2	1.715	2.173				1.000	1.000
	3	2.742	3.732					1.000
	4	1.704	3.353					
RoM Acc x	**0**	4.916	1.974	0.665				
	1	5.266	3.029					
	2	5.516	2.037					
	3	5.399	1.762					
	4	4.764	1.710					

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Table 10 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RoM Acc y	**0**	2.878	1.680	0.017	1.000	1.000	0.641	1.000
	1	3.146	4.899			0.829	0.006	0.370
	2	2.818	1.213				0.890	1.000
	3	4.367	2.288					1.000
	4	3.020	1.333					
RoM Acc z	**0**	6.895	1.784	0.127				
	1	6.752	4.308					
	2	8.132	2.344					
	3	7.415	2.955					
	4	7.655	2.248					
RoM Gyr x	**0**	39.251	25.329	0.016	0.144	0.048	0.401	0.019
	1	16.992	19.367			1.000	1.000	1.000
	2	14.014	18.324				1.000	1.000
	3	39.359	55.503					1.000
	4	10.318	20.244					
RoM Gyr y	**0**	107.946	36.206	0.001	0.170	0.048	0.013	0.001
	1	52.568	44.647			1.000	1.000	1.000
	2	37.176	45.195				1.000	1.000
	3	46.076	59.794					1.000
	4	25.480	50.039					
RoM Gyr z	**0**	28.141	14.005	0.009	1.000	0.019	0.203	0.013
	1	14.490	12.839			1.000	1.000	1.000
	2	9.376	11.862				1.000	1.000
	3	16.043	21.747					1.000
	4	7.483	14.616					
Pitch mean	**0**	-0.290	5.691	0.138				
	1	3.904	4.336					
	2	0.281	10.197					
	3	3.604	6.918					
	4	-1.222	5.254					
Pitch std	**0**	10.732	2.279	0.019	1.000	0.785	1.000	1.000
	1	9.511	3.103			0.059	1.000	0.090
	2	14.004	5.145				0.410	1.000
	3	10.717	5.356					0.572
	4	13.090	4.312					

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Table 10 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Roll mean	**0**	0.392	1.355	0.000	0.003	1.000	0.011	0.955
	1	-2.017	1.390			0.029	1.000	0.500
	2	-0.112	1.211				0.085	1.000
	3	-2.154	2.332					1.000
	4	-0.992	2.286					
Roll std	**0**	1.612	0.811	0.006	1.000	1.000	0.401	0.021
	1	1.813	0.621			1.000	1.000	0.099
	2	1.718	0.799				0.678	0.043
	3	2.799	1.822					1.000
	4	2.901	1.061					

Table 11: Descriptive statistics and results of the Kruskal-Wallis test for the task involving getting up from a chair.

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Duration of the activity	**0**	3.088	0.787	0.040	1.000	0.778	1.000	0.035
	1	3.519	0.725			1.000	1.000	1.000
	2	3.892	1.886				1.000	1.000
	3	3.773	2.334					0.239
	4	4.144	1.087					
Jerk mean Acc x	**0**	2.88E-05	1.17E-03	0.003	1.000	0.307	0.641	0.007
	1	-9.12E-05	4.79E-04			0.606	1.000	0.018
	2	-9.68E-04	3.55E-03				1.000	1.000
	3	-6.09E-04	2.13E-03					1.000
	4	-1.90E-03	1.96E-03					
Jerk mean Acc y	**0**	-7.02E-05	1.62E-03	0.025	0.939	1	0.385	0.282
	1	6.73E-04	9.96E-04			0.500	1.000	1.000
	2	1.26E-04	2.58E-03				0.186	0.132
	3	1.42E-03	2.04E-03					1.000
	4	9.63E-04	1.29E-03					
Jerk mean Acc z	**0**	-6.98E-03	3.27E-03	0.262				
	1	-5.11E-03	2.00E-03					
	2	-8.90E-03	7.68E-03					
	3	-5.75E-03	3.57E-03					
	4	-8.16E-03	5.10E-03					

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Table 11 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Jerk std Acc x	**0**	0.175	0.081	0.000	1.000	0.178	0.010	1.000
	1	0.136	0.038			0.002	0.000	0.087
	2	0.303	0.150				1.000	1.000
	3	0.432	0.253					0.480
	4	0.278	0.205					
Jerk std Acc y	**0**	0.160	0.128	0.000	0.190	1.000	0.007	1.000
	1	0.093	0.023			0.001	0.000	0.057
	2	0.189	0.082				0.520	1.000
	3	0.268	0.098					0.029
	4	0.171	0.120					
Jerk std Acc z	**0**	0.200	0.088	0.000	0.182	1.000	0.018	1.000
	1	0.129	0.035			0.002	0.000	0.016
	2	0.276	0.170				0.757	1.000
	3	0.370	0.161					0.203
	4	0.241	0.129					
RMS Acc x	**0**	9.464	0.082	0.041	1.000	1.000	0.385	1.000
	1	9.449	0.225			1.000	0.033	1.000
	2	9.197	0.950				0.691	1.000
	3	9.158	0.301					0.151
	4	9.461	0.138					
RMS Acc y	**0**	0.877	0.316	0.080				
	1	0.728	0.447					
	2	1.198	1.776					
	3	1.056	0.525					
	4	1.069	0.373					
RMS Acc z	**0**	2.131	0.960	0.005	1.000	0.500	0.007	0.194
	1	2.247	0.438			1.000	0.048	0.800
	2	2.735	0.830				1.000	1.000
	3	3.669	1.565					1.000
	4	2.979	1.203					
RMS Gyr x	**0**	6.157	2.485	0.030	0.114	0.141	0.453	0.033
	1	2.988	2.843			1.000	1.000	1.000
	2	2.539	3.179				1.000	1.000
	3	4.738	6.444					1.000
	4	1.931	3.837					

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Table 11 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RMS Gyr y	**0**	26.072	8.228	0.004	0.355	0.138	0.132	0.001
	1	14.271	12.028			1.000	1.000	0.814
	2	10.166	12.346				1.000	1.000
	3	11.992	16.240					1.000
	4	6.850	13.719					
RMS Gyr z	**0**	4.594	2.885	0.020	0.540	0.135	0.162	0.013
	1	2.438	2.155			1.000	1.000	1.000
	2	1.911	2.410				1.000	1.000
	3	1.945	2.574					1.000
	4	1.597	3.173					
RoM Acc x	**0**	5.539	2.031	0.002	0.572	1.000	1.000	0.128
	1	4.313	1.346			0.075	0.194	1.000
	2	7.048	4.440				1.000	0.011
	3	6.119	2.421					0.035
	4	4.404	3.206					
RoM Acc y	**0**	3.075	3.104	0.001	0.691	1.000	0.248	1.000
	1	1.807	0.504			0.010	0.000	0.500
	2	3.328	2.176				1.000	1.000
	3	3.183	0.878					0.355
	4	2.657	1.566					
RoM Acc z	**0**	6.767	2.465	0.003	1.000	0.704	0.040	1.000
	1	5.875	1.277			0.148	0.004	1.000
	2	8.417	3.054				1.000	1.000
	3	8.900	2.231					0.370
	4	7.089	2.471					
RoM Gyr x	**0**	37.886	16.480	0.004	0.046	0.049	0.730	0.003
	1	15.582	14.269			1.000	1.000	1.000
	2	13.604	17.688				1.000	1.000
	3	28.459	36.448					0.678
	4	9.398	19.120					
RoM Gyr y	**0**	115.779	37.030	0.003	0.389	0.045	0.341	0.001
	1	65.794	55.746			1.000	1.000	0.793
	2	43.521	53.067				1.000	1.000
	3	52.583	67.510					0.89
	4	29.864	58.714					

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Table 11 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RoM Gyr z	0	23.773	14.567	0.024	0.462	0.208	0.471	0.011
	1	12.005	10.572			1.000	1.000	1.000
	2	9.846	12.245				1.000	1.000
	3	11.213	14.059					1.000
	4	7.713	15.351					
Pitch mean	0	14.179	3.594	0.296				
	1	12.880	2.149					
	2	17.426	13.042					
	3	14.323	9.398					
	4	18.441	10.204					
Pitch std	0	8.596	1.977	0.023	1.000	0.037	1.000	1.000
	1	8.516	1.937			0.046	1.000	1.000
	2	13.294	6.284				1.000	0.362
	3	10.426	4.070					1.000
	4	9.569	3.849					
Roll mean	0	-0.059	2.549	0.003	1.000	1.000	0.327	0.046
	1	-0.050	1.359			1.000	0.691	0.120
	2	2.434	14.097				0.104	0.011
	3	1.699	2.334					1.000
	4	2.099	3.635					
Roll std	0	1.484	0.838	0.426				
	1	1.574	0.686					
	2	3.748	8.603					
	3	1.826	1.177					
	4	2.074	0.765					

Table 12: Descriptive statistics and results of the Kruskal-Wallis test for the task involving lying on a bed.

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Duration of the activity	0	5.189	0.653	0.000	1.000	0.947	0.000	0.014
	1	6.611	2.756			1.000	0.013	1.000
	2	6.855	2.663				0.019	1.000
	3	12.348	5.320					1.000
	4	8.539	3.630					

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Table 12 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Jerk mean Acc x	**0**	1.70E-02	3.03E-03	0.000	0.520	0.000	0.000	0.034
	1	1.33E-02	4.76E-03			0.123	0.120	1.000
	2	4.78E-03	1.18E-02				1.000	1.000
	3	8.07E-03	5.27E-03					1.000
	4	1.15E-02	4.41E-03					
Jerk mean Acc y	**0**	2.79E-03	1.78E-02	0.727				
	1	4.42E-03	1.59E-02					
	2	7.46E-03	1.24E-02					
	3	6.50E-03	5.74E-03					
	4	1.06E-02	3.91E-03					
Jerk mean Acc z	**0**	3.70E-03	6.09E-03	0.014	1.000	0.101	1.000	1.000
	1	4.53E-03	2.12E-03			0.009	0.653	1.000
	2	7.10E-04	2.46E-03				1.000	0.393
	3	2.39E-03	3.29E-03					1.000
	4	3.28E-03	2.07E-03					
Jerk std Acc x	**0**	0.253	0.106	0.047	0.264	0.972	1.000	1.000
	1	0.178	0.064			1.000	0.087	1.000
	2	0.185	0.051				0.393	1.000
	3	0.337	0.206					1.000
	4	0.253	0.140					
Jerk std Acc y	**0**	0.322	0.147	0.007	0.009	0.054	1.000	0.453
	1	0.169	0.041			1.000	0.294	1.000
	2	0.184	0.055				1.000	1.000
	3	0.242	0.100					1.000
	4	0.247	0.167					
Jerk std Acc z	**0**	0.303	0.152	0.006	0.059	0.020	1.000	1.000
	1	0.187	0.102			1.000	0.276	1.000
	2	0.161	0.033				0.111	1.000
	3	0.304	0.181					1.000
	4	0.230	0.114					
RMS Acc x	**0**	6.381	0.741	0.048	1.000	0.032	0.362	0.540
	1	6.754	0.791			1.000	1.000	1.000
	2	7.262	0.625				1.000	1.000
	3	7.024	1.145					1.000
	4	6.977	0.776					

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Table 12 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RMS Acc y	0	7.008	0.807	0.009	1.000	0.075	0.178	0.014
	1	6.615	0.782			1.000	1.000	0.355
	2	6.159	0.626				1.000	1.000
	3	4.825	2.938					1.000
	4	5.890	0.733					
RMS Acc z	0	3.420	0.745	0.002	1.000	0.237	1.000	1.000
	1	2.964	1.185			1.000	0.704	0.062
	2	2.529	0.745				0.050	0.002
	3	4.043	1.703					1.000
	4	4.459	1.685					
RMS Gyr x	0	16.948	9.367	0.000	0.248	0.001	0.004	0.004
	1	8.323	7.154			0.814	1.000	1.000
	2	2.974	3.811				1.000	1.000
	3	6.133	7.702					1.000
	4	2.366	4.645					
RMS Gyr y	0	22.799	4.423	0.000	0.051	0.000	0.000	0.000
	1	11.985	10.016			0.561	0.771	0.859
	2	5.674	7.222				1.000	1.000
	3	5.279	6.368					1.000
	4	3.988	7.569					
RMS Gyr z	0	28.592	4.990	0.000	0.155	0.000	0.000	0.000
	1	13.494	12.103			0.435	0.059	0.020
	2	6.669	8.541				1.000	1.000
	3	5.126	7.283					1.000
	4	3.401	6.521					
RoM Acc x	0	12.276	1.617	0.009	1.000	0.073	1.000	1.000
	1	11.414	3.031			0.800	1.000	0.972
	2	9.818	1.540				0.109	0.007
	3	12.823	5.878					1.000
	4	13.342	3.117					
RoM Acc y	0	13.572	3.684	0.008	1.000	0.029	0.348	0.166
	1	11.888	1.623			0.083	0.771	0.401
	2	10.195	0.986				1.000	1.000
	3	9.734	3.340					1.000
	4	10.622	1.360					

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Table 12 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RoM Acc z	**0**	9.124	2.441	0.002	1.000	0.029	1.000	1.000
	1	8.320	2.360			0.313	0.704	1.000
	2	6.334	1.763				0.001	0.096
	3	11.224	4.971					1.000
	4	8.671	2.027					
RoM Gyr x	**0**	104.851	62.912	0.000	0.227	0.000	0.031	0.002
	1	47.959	42.281			0.471	1.000	1.000
	2	18.701	24.196				1.000	1.000
	3	43.307	54.715					1.000
	4	9.889	17.868					
RoM Gyr y	**0**	123.028	40.503	0.000	0.135	0.000	0.009	0.002
	1	64.777	55.102			0.253	1.000	1.000
	2	31.711	39.034				1.000	1.000
	3	41.829	52.599					1.000
	4	24.487	46.037					
RoM Gyr z	**0**	93.749	31.645	0.000	0.288	0.000	0.001	0.000
	1	48.314	43.767			0.123	0.800	0.276
	2	23.686	30.776				1.000	1.000
	3	29.800	38.735					1.000
	4	12.390	22.681					
Pitch mean	**0**	-17.673	8.559	0.000	0.972	0.000	1.000	1.000
	1	-12.484	14.900			0.075	1.000	0.540
	2	12.592	30.898				0.000	0.000
	3	-23.236	19.951					1.000
	4	-23.908	18.008					
Pitch std	**0**	28.870	19.024	0.006	1.000	0.248	1.000	1.000
	1	20.779	20.240			1.000	0.070	1.000
	2	18.998	19.532				0.005	0.510
	3	39.092	22.835					1.000
	4	31.755	21.689					
Roll mean	**0**	5.162	45.936	0.650				
	1	11.199	40.065					
	2	15.438	33.143					
	3	26.085	20.914					
	4	33.998	9.664					

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Table 12 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Roll std	**0**	35.064	3.304	0.148				
	1	33.470	5.112					
	2	29.838	5.669					
	3	24.825	13.956					
	4	34.031	5.526					

Table 13: Descriptive statistics and results of the Kruskal-Wallis test for the task involving getting from a bed.

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Duration of the activity	**0**	5.563	0.867	0.001	1.000	1.000	0.001	0.010
	1	6.651	1.572			1.000	0.224	0.972
	2	6.840	2.088				0.188	0.844
	3	10.079	3.978					1.000
	4	8.527	2.611					
Jerk mean Acc x	**0**	-1.63E-02	4.33E-03	0.001	0.393	0.002	0.003	0.045
	1	-1.22E-02	3.73E-03			0.955	1.000	1.000
	2	-6.82E-03	9.32E-03				1.000	1.000
	3	-1.05E-02	7.31E-03					1.000
	4	-1.10E-02	3.16E-03					
Jerk mean Acc y	**0**	-3.70E-03	1.65E-02	0.735				
	1	-3.27E-03	1.48E-02					
	2	-8.95E-03	9.67E-03					
	3	-7.68E-03	8.27E-03					
	4	-9.54E-03	3.17E-03					
Jerk mean Acc z	**0**	-3.33E-03	5.30E-03	0.091				
	1	-4.34E-03	1.64E-03					
	2	-1.08E-03	2.69E-03					
	3	-2.33E-03	5.01E-03					
	4	-2.61E-03	1.63E-03					
Jerk std Acc x	**0**	0.186	0.048	0.001	0.072	1.000	1.000	0.730
	1	0.124	0.050			0.037	0.004	1.000
	2	0.229	0.164				1.000	0.444
	3	0.301	0.211					0.087
	4	0.144	0.061					

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Table 13 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Jerk std Acc y	**0**	0.190	0.064	0.007	0.028	1.000	1.000	0.771
	1	0.121	0.043			0.081	0.025	1.000
	2	0.188	0.076				1.000	1.000
	3	0.287	0.272					0.717
	4	0.146	0.053					
Jerk std Acc z	**0**	0.201	0.038	0.001	0.008	1.000	1.000	0.044
	1	0.135	0.048			0.227	0.023	1.000
	2	0.190	0.074				1.000	0.785
	3	0.257	0.156					0.114
	4	0.149	0.047					
RMS Acc x	**0**	7.664	0.393	0.185				
	1	8.104	0.393					
	2	7.958	0.832					
	3	7.678	0.902					
	4	7.806	0.490					
RMS Acc y	**0**	5.498	0.542	0.453				
	1	4.919	0.615					
	2	5.137	1.424					
	3	4.202	2.479					
	4	5.189	0.735					
RMS Acc z	**0**	2.966	0.669	0.051				
	1	2.698	0.824					
	2	2.567	0.486					
	3	3.583	1.646					
	4	3.776	1.423					
RMS Gyr x	**0**	12.370	5.792	0.000	0.155	0.001	0.222	0.000
	1	7.221	6.281			1.000	1.000	0.334
	2	2.833	3.560				1.000	1.000
	3	4.921	6.205					0.237
	4	1.453	2.711					
RMS Gyr y	**0**	20.670	6.164	0.000	0.341	0.001	0.006	0.000
	1	11.156	9.727			0.859	1.000	0.075
	2	6.425	7.904				1.000	1.000
	3	6.126	7.502					1.000
	4	3.500	6.789					

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Table 13 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RMS Gyr z	**0**	23.655	4.393	0.000	0.065	0.001	0.000	0.000
	1	10.330	9.146			1.000	0.203	0.015
	2	6.610	8.228				1.000	0.629
	3	4.143	5.302					1.000
	4	1.902	3.450					
RoM Acc x	**0**	11.237	1.457	0.024	0.150	0.135	1.000	1.000
	1	9.241	2.314			1.000	0.242	1.000
	2	9.229	1.974				0.220	1.000
	3	10.715	3.017					1.000
	4	10.218	2.078					
RoM Acc y	**0**	11.602	2.107	0.052				
	1	10.712	1.406					
	2	9.627	1.375					
	3	9.080	4.100					
	4	9.545	1.150					
RoM Acc z	**0**	8.788	1.293	0.000	1.000	0.008	1.000	0.048
	1	8.150	2.156			0.075	0.215	0.320
	2	6.262	0.845				0.000	1.000
	3	10.860	2.416					0.000
	4	6.529	1.868					
RoM Gyr x	**0**	65.903	31.912	0.000	0.217	0.003	0.672	0.000
	1	38.497	34.630			1.000	1.000	0.567
	2	15.330	20.025				0.685	1.000
	3	29.091	36.147					0.178
	4	8.498	16.231					
RoM Gyr y	**0**	95.919	39.512	0.000	0.691	0.018	0.109	0.000
	1	57.598	52.046			1.000	1.000	0.075
	2	34.653	42.531				1.000	1.000
	3	34.536	41.689					0.520
	4	17.182	33.229					
RoM Gyr z	**0**	67.796	14.144	0.000	0.079	0.002	0.000	0.000
	1	31.465	28.673			1.000	1.000	0.025
	2	21.182	27.959				1.000	0.500
	3	19.820	24.082					1.000
	4	6.447	11.587					

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Table 13 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Pitch mean	**0**	58.915	53.196	0.000	1.000	0.000	1.000	1.000
	1	31.142	43.525			0.025	1.000	1.000
	2	0.229	13.208				0.000	0.001
	3	66.894	57.260					1.000
	4	66.818	56.676					
Pitch std	**0**	30.622	22.878	0.003	0.435	0.009	1.000	1.000
	1	17.552	18.709			1.000	0.444	1.000
	2	13.926	15.052				0.010	0.282
	3	32.038	20.512					1.000
	4	30.309	21.930					
Roll mean	**0**	-10.210	55.239	0.111				
	1	-13.822	53.537					
	2	-28.756	32.074					
	3	-36.464	22.482					
	4	-51.604	11.672					
Roll std	**0**	33.137	2.221	0.024	0.595	0.040	0.034	0.435
	1	28.991	5.619			1.000	1.000	1.000
	2	26.145	8.787				1.000	1.000
	3	22.148	13.041					1.000
	4	29.057	5.231					

Table 14: Descriptive statistics and results of the Kruskal-Wallis test for the task involving walking.

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Duration of the activity	**0**	10.011	0.516	0.000	1.000	1.000	0.040	0.000
	1	11.220	2.699			1.000	0.351	0.004
	2	10.662	0.959				1.000	0.032
	3	16.033	7.888					1.000
	4	18.923	5.747					
Jerk mean Acc x	**0**	7.64E-05	1.98E-04	0.475				
	1	3.57E-05	1.54E-04					
	2	5.22E-05	2.58E-04					
	3	-5.71E-05	5.94E-04					
	4	-4.08E-05	1.07E-04					

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Table 14 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Jerk mean Acc y	**0**	1.94E-04	4.53E-04	0.731				
	1	1.49E-05	3.05E-04					
	2	4.81E-05	2.87E-04					
	3	-2.00E-05	2.93E-04					
	4	-1.56E-05	2.75E-04					
Jerk mean Acc z	**0**	-7.05E-05	6.06E-04	0.322				
	1	-1.13E-04	4.36E-04					
	2	-3.28E-04	3.09E-04					
	3	-2.66E-04	6.02E-04					
	4	-3.97E-05	3.49E-04					
Jerk std Acc x	**0**	0.651	0.180	0.000	1.000	0.490	1.000	0.003
	1	0.550	0.149			1.000	1.000	0.081
	2	0.498	0.089				0.111	0.906
	3	0.773	0.342					0.000
	4	0.384	0.154					
Jerk std Acc y	**0**	0.664	0.275	0.000	1.000	1.000	1.000	0.000
	1	0.542	0.170			1.000	1.000	0.000
	2	0.495	0.077				1.000	0.010
	3	0.597	0.231					0.000
	4	0.289	0.074					
Jerk std Acc z	**0**	0.829	0.315	0.000	1.000	0.595	1.000	0.000
	1	0.743	0.327			1.000	1.000	0.001
	2	0.602	0.132				1.000	0.155
	3	0.751	0.281					0.001
	4	0.386	0.137					
RMS Acc x	**0**	9.818	0.223	0.003	1.000	1.000	0.320	0.033
	1	9.750	0.062			1.000	1.000	0.814
	2	9.835	0.097				0.104	0.008
	3	9.630	0.344					1.000
	4	9.641	0.171					
RMS Acc y	**0**	1.535	0.562	0.000	1.000	1.000	0.042	0.641
	1	1.465	0.485			1.000	0.033	0.540
	2	1.311	0.149				0.001	0.034
	3	1.977	0.329					1.000
	4	1.859	0.560					

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Table 14 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RMS Acc z	**0**	2.416	1.210	0.008	1.000	1.000	0.085	1.000
	1	2.140	0.487			1.000	0.077	1.000
	2	1.940	0.326				0.014	0.500
	3	3.228	1.415					1.000
	4	2.549	0.972					
RMS Gyr x	**0**	19.856	3.884	0.000	0.348	0.004	0.001	0.000
	1	10.487	9.732			1.000	0.859	0.111
	2	7.169	9.040				1.000	1.000
	3	6.932	8.677					1.000
	4	3.636	6.838					
RMS Gyr y	**0**	15.061	6.258	0.000	0.208	0.024	0.166	0.000
	1	9.183	9.212			1.000	1.000	0.051
	2	5.950	7.401				1.000	0.385
	3	4.929	5.838					0.066
	4	1.583	2.824					
RMS Gyr z	**0**	16.115	2.562	0.000	0.208	0.002	0.000	0.000
	1	8.299	8.020			1.000	0.385	0.002
	2	4.825	5.800				1.000	0.190
	3	3.078	3.626					1.000
	4	2.143	4.085					
RoM Acc x	**0**	12.394	3.698	0.000	0.313	1.000	1.000	0.000
	1	9.277	1.619			1.000	0.253	0.453
	2	9.722	1.331				1.000	0.066
	3	12.581	4.256					0.000
	4	7.651	1.380					
RoM Acc y	**0**	11.310	5.721	0.001	1.000	1.000	1.000	0.003
	1	9.344	3.501			1.000	1.000	0.031
	2	8.482	1.635				1.000	0.052
	3	10.412	3.395					0.001
	4	6.242	1.215					
RoM Acc z	**0**	12.872	6.101	0.000	1.000	1.000	1.000	0.002
	1	11.200	4.333			1.000	1.000	0.004
	2	9.414	2.894				1.000	0.294
	3	11.296	3.337					0.002
	4	6.566	2.500					

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Table 14 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RoM Gyr x	0	139.282	70.522	0.000	0.385	0.010	0.019	0.000
	1	61.042	55.028			1.000	1.000	0.186
	2	40.850	50.303				1.000	1.000
	3	50.775	62.997					1.000
	4	20.513	38.064					
RoM Gyr y	0	108.474	55.288	0.000	0.158	0.015	0.520	0.000
	1	66.599	67.354			1.000	1.000	0.282
	2	36.885	44.809				1.000	1.000
	3	40.910	50.930					0.077
	4	11.308	20.082					
RoM Gyr z	0	101.035	23.356	0.000	0.288	0.006	0.001	0.000
	1	56.870	55.170			1.000	0.837	0.001
	2	30.376	36.182				1.000	0.110
	3	25.173	30.606					0.381
	4	13.331	25.335					
Pitch mean	0	0.029	2.138	0.374				
	1	0.955	1.700					
	2	1.070	1.269					
	3	1.782	3.416					
	4	1.389	1.486					
Pitch std	0	2.201	0.466	0.000	0.418	0.028	1.000	1.000
	1	1.819	0.352			1.000	0.007	1.000
	2	1.680	0.345				0.000	0.186
	3	2.737	0.976					0.471
	4	2.022	0.384					
Roll mean	0	0.820	1.106	0.005	1.000	0.044	0.056	1.000
	1	0.360	0.625			0.771	0.906	1.000
	2	-0.383	0.854				1.000	0.083
	3	-0.379	1.521					0.104
	4	0.598	1.001					
Roll std	0	1.805	0.303	0.165				
	1	1.656	0.374					
	2	1.560	0.281					
	3	1.636	0.737					
	4	1.510	0.458					

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Table 14 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Step length	**0**	0.636	0.088	0.000	1.000	1.000	0.096	0.000
	1	0.591	0.100			1.000	1.000	0.006
	2	0.665	0.113				0.029	0.000
	3	0.531	0.064					0.385
	4	0.455	0.043					
Stride length	**0**	1.255	0.162	0.000	1.000	1.000	0.186	0.000
	1	1.181	0.195			1.000	1.000	0.006
	2	1.324	0.229				0.041	0.000
	3	1.069	0.135					0.313
	4	0.910	0.088					
Velocity	**0**	1.195	0.150	0.000	1.000	1.000	0.054	0.000
	1	1.087	0.182			1.000	1.000	0.002
	2	1.190	0.191				0.106	0.000
	3	0.968	0.188					0.096
	4	0.766	0.081					
Cadence	**0**	113.300	4.411	0.061				
	1	111.517	12.528					
	2	108.274	8.324					
	3	110.149	9.085					
	4	102.471	17.794					
Number of steps	**0**	13.000	1.464	0.000	0.932	1.000	0.000	0.000
	1	16.067	4.415			1.000	0.070	0.003
	2	14.700	2.644				0.017	0.000
	3	22.800	8.546					1.000
	4	25.200	6.753					
Step time	**0**	0.533	0.021	0.071				
	1	0.550	0.062					
	2	0.560	0.043					
	3	0.582	0.129					
	4	0.607	0.094					
Stride time	**0**	1.066	0.039	0.063				
	1	1.095	0.123					
	2	1.119	0.086					
	3	1.165	0.254					
	4	1.212	0.188					

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Table 14 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Stance time	**0**	0.645	0.046	0.016	1.000	0.972	0.410	0.006
	1	0.688	0.072			1.000	1.000	0.551
	2	0.693	0.073				1.000	0.744
	3	0.704	0.079					1.000
	4	0.777	0.136					
Swing time	**0**	0.420	0.037	0.135				
	1	0.407	0.063					
	2	0.426	0.047					
	3	0.461	0.258					
	4	0.435	0.056					
Double support phase	**0**	21.090	6.535	0.001	0.109	1.000	0.007	0.005
	1	25.509	4.930			1.000	1.000	1.000
	2	23.765	6.883				0.313	0.237
	3	28.249	6.537					1.000
	4	27.644	4.021					
Stance phase	**0**	60.568	3.430	0.004	0.094	1.000	0.037	0.008
	1	62.974	2.842			1.000	1.000	1.000
	2	61.882	3.463				0.678	0.237
	3	61.479	10.943					1.000
	4	63.991	1.946					
Swing phase	**0**	38.580	4.221	0.003	0.174	1.000	0.174	0.001
	1	35.369	3.785			1.000	1.000	1.000
	2	36.389	4.209				1.000	0.194
	3	39.723	19.640					1.000
	4	33.347	2.482					
AS step length	**0**	1.09E-01	6.52E-02	0.022	1.000	1.000	0.653	1.000
	1	1.32E-01	1.02E-01			0.829	0.444	1.000
	2	7.00E-02	4.62E-02				1.000	0.123
	3	6.75E-02	5.39E-02					0.054
	4	1.39E-01	7.61E-02					
AS step time	**0**	2.44E-02	2.27E-02	0.220				
	1	3.20E-02	4.73E-02					
	2	3.49E-02	2.58E-02					
	3	6.48E-02	1.03E-01					
	4	4.42E-02	3.20E-02					

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Table 14 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
AS velocity	0	2.13E-01	1.17E-01	0.021	1.000	0.510	1.000	1.000
	1	2.30E-01	1.26E-01			0.270	1.000	1.000
	2	1.30E-01	7.80E-02				1.000	0.034
	3	1.65E-01	1.37E-01					0.203
	4	2.64E-01	1.25E-01					
AS stance time	0	2.03E-02	1.86E-02	0.499				
	1	2.65E-02	3.16E-02					
	2	2.68E-02	1.52E-02					
	3	1.19E-01	3.71E-01					
	4	3.30E-02	3.37E-02					
AS swing time	0	1.96E-02	1.54E-02	0.253				
	1	2.13E-02	2.44E-02					
	2	2.71E-02	1.41E-02					
	3	1.19E-01	3.75E-01					
	4	3.30E-02	3.43E-02					
SD step length	0	9.11E-02	2.98E-02	0.007	1.000	0.199	1.000	1.000
	1	9.40E-02	4.58E-02			0.757	1.000	1.000
	2	6.52E-02	2.25E-02				0.012	0.015
	3	1.12E-01	5.84E-02					1.000
	4	1.00E-01	3.01E-02					
SD step time	0	3.82E-02	2.05E-02	0.002	1.000	1.000	0.035	0.064
	1	4.95E-02	2.16E-02			0.751	1.000	1.000
	2	3.74E-02	1.72E-02				0.019	0.036
	3	1.77E-01	4.45E-01					1.000
	4	6.10E-02	2.19E-02					
SD step velocity	0	1.72E-01	5.46E-02	0.000	1.000	0.081	0.989	1.000
	1	1.74E-01	6.43E-02			0.066	1.000	1.000
	2	1.17E-01	3.43E-02				0.000	0.014
	3	2.01E-01	5.16E-02					1.000
	4	1.79E-01	4.74E-02					
SD stance time	0	3.50E-02	1.80E-02	0.005	0.453	1.000	0.065	0.007
	1	4.66E-02	1.62E-02			1.000	1.000	1.000
	2	4.22E-02	1.65E-02				0.717	0.132
	3	2.35E-01	6.88E-01					1.000
	4	6.28E-02	2.35E-02					

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Table 14 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
SD swing time	0	3.43E-02	1.92E-02	0.025	1.000	1.000	0.114	0.248
	1	4.08E-02	1.74E-02			1.000	1.000	1.000
	2	3.35E-02	1.57E-02				0.144	0.307
	3	2.27E-01	6.85E-01					1.000
	4	5.62E-02	2.98E-02					

Table 15: Descriptive statistics and results of the Kruskal-Wallis test for the task involving turning 180°.

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Duration of the activity	0	68.540	2.845	0.019	1.000	0.857	0.143	0.017
	1	77.258	18.111			1.000	1.000	0.392
	2	77.324	3.661				1.000	1.000
	3	110.876	49.430					1.000
	4	149.038	73.832					
Jerk mean Acc x	0	3.21E-05	4.20E-05	0.088				
	1	1.10E-06	1.04E-05					
	2	2.33E-06	3.52E-05					
	3	-1.25E-05	2.74E-05					
	4	-3.23E-05	3.97E-05					
Jerk mean Acc y	0	5.97E-05	1.19E-04	0.467				
	1	-8.90E-06	9.42E-05					
	2	4.03E-05	6.77E-05					
	3	1.18E-05	5.61E-05					
	4	-2.14E-06	8.02E-06					
Jerk mean Acc z	0	-3.47E-06	9.11E-05	0.940				
	1	-2.58E-05	3.56E-05					
	2	-1.85E-05	5.28E-05					
	3	-6.90E-07	5.38E-05					
	4	-2.85E-05	9.38E-05					
Jerk std Acc x	0	0.729	0.193	0.087				
	1	0.719	0.161					
	2	0.531	0.073					
	3	0.780	0.402					
	4	0.437	0.165					

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Table 15 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Jerk std Acc y	**0**	0.728	0.337	0.081				
	1	0.687	0.214					
	2	0.530	0.097					
	3	0.555	0.203					
	4	0.360	0.128					
Jerk std Acc z	**0**	0.907	0.366	0.072				
	1	0.943	0.416					
	2	0.623	0.134					
	3	0.728	0.329					
	4	0.445	0.157					
RMS Acc x	**0**	9.856	0.224	0.334				
	1	9.808	0.055					
	2	9.852	0.075					
	3	9.731	0.163					
	4	9.656	0.215					
RMS Acc y	**0**	1.623	0.604	0.378				
	1	1.664	0.559					
	2	1.343	0.156					
	3	1.804	0.470					
	4	1.949	0.598					
RMS Acc z	**0**	2.503	1.364	0.775				
	1	2.373	0.570					
	2	1.987	0.318					
	3	2.587	0.895					
	4	2.536	0.990					
RMS Gyr x	**0**	40.090	4.862	0.009	1.000	0.392	0.068	0.009
	1	22.848	22.317			1.000	1.000	0.317
	2	14.326	18.794				1.000	1.000
	3	10.592	13.949					1.000
	4	5.029	10.207					
RMS Gyr y	**0**	17.819	8.077	0.074				
	1	11.973	13.034					
	2	6.903	9.001					
	3	5.452	6.889					
	4	1.787	3.425					

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Table 15 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RMS Gyr z	**0**	19.326	4.213	0.010	1.000	0.392	0.068	0.011
	1	10.568	10.984			1.000	1.000	0.392
	2	5.462	7.110				1.000	1.000
	3	3.374	4.244					1.000
	4	2.509	5.152					
RoM Acc x	**0**	13.647	3.481	0.103				
	1	13.426	3.093					
	2	11.561	1.625					
	3	15.005	2.984					
	4	9.863	2.217					
RoM Acc y	**0**	13.404	6.571	0.310				
	1	13.956	4.919					
	2	11.003	2.057					
	3	11.877	2.319					
	4	9.366	1.951					
RoM Acc z	**0**	15.826	6.337	0.119				
	1	16.642	6.324					
	2	11.473	2.176					
	3	14.549	2.693					
	4	9.877	3.246					
RoM Gyr x	**0**	301.878	92.796	0.009	1.000	0.481	0.060	0.013
	1	176.929	173.183			1.000	0.938	0.317
	2	100.909	132.004				1.000	1.000
	3	87.844	115.153					1.000
	4	37.466	75.515					
RoM Gyr y	**0**	146.376	85.013	0.163				
	1	105.590	118.116					
	2	54.861	73.089					
	3	56.979	72.720					
	4	16.109	30.763					
RoM Gyr z	**0**	126.070	34.542	0.009	1.000	0.938	0.099	0.011
	1	85.830	85.008			1.000	0.857	0.161
	2	41.959	54.277				1.000	1.000
	3	33.857	43.576					1.000
	4	17.673	35.724					

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Table 15 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Pitch mean	**0**	-0.788	3.839	0.898				
	1	1.033	3.300					
	2	0.261	1.525					
	3	1.913	4.402					
	4	1.291	2.293					
Pitch std	**0**	2.474	0.709	0.081				
	1	2.463	0.814					
	2	2.312	0.201					
	3	3.289	0.343					
	4	2.433	0.254					
Roll mean	**0**	1.174	1.108	0.196				
	1	-0.405	1.378					
	2	-0.142	0.744					
	3	-0.679	1.378					
	4	0.912	1.535					
Roll std	**0**	3.286	0.792	0.068				
	1	2.811	1.266					
	2	1.866	0.443					
	3	2.028	0.362					
	4	1.808	0.376					

Table 16: Descriptive statistics and results of the Kruskal-Wallis test for the task involving turning 90° to the right.

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Duration of the activity	**0**	11.743	1.554	0.000	0.792	0.471	0.017	0.000
	1	14.007	3.323			1.000	1.000	0.007
	2	13.659	1.411				1.000	0.016
	3	17.723	6.751					0.466
	4	21.502	5.397					
Jerk mean Acc x	**0**	5.86E-05	1.58E-04	0.528				
	1	-8.46E-06	1.42E-04					
	2	-8.35E-06	1.68E-04					
	3	-2.89E-05	1.85E-04					
	4	4.32E-05	9.53E-05					

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Table 16 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Jerk mean Acc y	**0**	1.70E-04	3.90E-04	0.159				
	1	-1.19E-04	3.39E-04					
	2	-1.02E-04	4.28E-04					
	3	5.59E-05	3.33E-04					
	4	6.80E-05	3.69E-04					
Jerk mean Acc z	**0**	3.20E-05	4.67E-04	0.002	1.000	1.000	0.253	1.000
	1	-1.08E-04	2.77E-04			1.000	1.000	0.199
	2	-1.94E-04	2.96E-04				1.000	0.039
	3	-4.14E-04	5.35E-04					0.002
	4	1.72E-04	2.22E-04					
Jerk std Acc x	**0**	0.683	0.209	0.000	1.000	0.348	1.000	0.006
	1	0.631	0.137			0.583	1.000	0.012
	2	0.498	0.075				0.128	1.000
	3	0.826	0.417					0.001
	4	0.435	0.148					
Jerk std Acc y	**0**	0.691	0.327	0.001	1.000	1.000	1.000	0.004
	1	0.593	0.150			1.000	1.000	0.002
	2	0.509	0.113				1.000	0.182
	3	0.573	0.265					0.081
	4	0.360	0.142					
Jerk std Acc z	**0**	0.845	0.335	0.001	1.000	0.418	1.000	0.002
	1	0.831	0.299			0.410	1.000	0.002
	2	0.596	0.189				1.000	0.859
	3	0.733	0.370					0.199
	4	0.447	0.151					
RMS Acc x	**0**	9.842	0.260	0.015	1.000	1.000	1.000	0.155
	1	9.764	0.094			0.800	1.000	1.000
	2	9.847	0.062				0.300	0.013
	3	9.738	0.154					1.000
	4	9.660	0.199					
RMS Acc y	**0**	1.563	0.590	0.000	1.000	1.000	0.041	0.471
	1	1.556	0.475			1.000	0.083	0.800
	2	1.295	0.177				0.000	0.009
	3	1.949	0.245					1.000
	4	1.910	0.544					

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Table 16 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RMS Acc z	**0**	2.469	1.272	0.391				
	1	2.263	0.492					
	2	2.042	0.243					
	3	2.557	1.015					
	4	2.551	0.945					
RMS Gyr x	**0**	24.830	4.135	0.000	0.378	0.015	0.000	0.000
	1	14.100	12.762			1.000	0.378	0.026
	2	9.262	11.295				1.000	0.540
	3	8.078	9.894					1.000
	4	4.301	8.191					
RMS Gyr y	**0**	17.313	7.129	0.000	0.378	0.062	0.077	0.000
	1	10.606	10.690			1.000	1.000	0.026
	2	7.376	8.961				1.000	0.190
	3	4.890	5.651					0.155
	4	1.639	2.884					
RMS Gyr z	**0**	18.016	3.896	0.000	0.186	0.002	0.000	0.000
	1	8.920	8.660			1.000	0.270	0.007
	2	5.274	6.423				1.000	0.435
	3	3.061	3.568					1.000
	4	2.413	4.593					
RoM Acc x	**0**	12.436	3.525	0.000	1.000	0.235	1.000	0.000
	1	10.295	1.667			1.000	0.520	0.086
	2	9.688	1.254				0.062	0.666
	3	13.089	4.227					0.000
	4	8.311	1.317					
RoM Acc y	**0**	10.952	5.842	0.030	1.000	1.000	1.000	0.485
	1	10.393	3.002			1.000	1.000	0.026
	2	8.971	1.998				1.000	0.397
	3	10.127	3.344					0.096
	4	7.472	1.591					
RoM Acc z	**0**	12.508	4.636	0.001	1.000	0.294	1.000	0.010
	1	12.601	4.112			0.144	1.000	0.004
	2	9.289	3.491				0.939	1.000
	3	10.696	2.938					0.054
	4	7.564	2.510					

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Table 16 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RoM Gyr x	**0**	157.314	65.453	0.000	0.859	0.026	0.021	0.000
	1	80.995	70.509			1.000	1.000	0.013
	2	52.901	64.874				1.000	0.540
	3	58.674	73.945					0.629
	4	23.154	43.815					
RoM Gyr y	**0**	114.015	52.381	0.000	0.341	0.018	0.300	0.000
	1	80.144	82.523			1.000	1.000	0.087
	2	45.681	58.269				1.000	1.000
	3	39.219	47.317					0.101
	4	11.119	19.336					
RoM Gyr z	**0**	110.804	30.704	0.000	0.444	0.005	0.000	0.000
	1	64.819	61.291			1.000	0.237	0.003
	2	32.601	39.773				1.000	0.327
	3	23.719	28.293					1.000
	4	14.889	28.082					
Pitch mean	**0**	-1.050	2.404	0.045	0.057	1.000	1.000	0.138
	1	1.407	2.025			1.000	1.000	1.000
	2	0.163	1.607				1.000	1.000
	3	1.630	3.698					1.000
	4	0.389	0.889					
Pitch std	**0**	2.114	0.589	0.001	1.000	1.000	0.170	1.000
	1	1.865	0.511			1.000	0.002	1.000
	2	1.789	0.184				0.002	1.000
	3	2.806	1.011					0.307
	4	1.992	0.286					
Roll mean	**0**	0.698	1.133	0.001	0.629	0.111	0.068	1.000
	1	-0.181	1.229			1.000	1.000	0.151
	2	-0.431	0.935				1.000	0.019
	3	-0.495	1.453					0.011
	4	0.933	1.013					
Roll std	**0**	2.218	0.456	0.000	1.000	0.013	0.000	0.001
	1	1.887	0.362			0.922	0.012	0.151
	2	1.619	0.235				1.000	1.000
	3	1.446	0.103					1.000
	4	1.508	0.398					

Table 17: Descriptive statistics and results of the Kruskal-Wallis test for the task involving turning 90° to the left.

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Duration of the activity	0	11.649	1.215	0.000	0.814	0.288	0.013	0.000
	1	13.844	3.104			1.000	1.000	0.004
	2	13.546	1.332				1.000	0.021
	3	17.517	6.381					0.409
	4	22.439	7.040					
Jerk mean Acc x	0	7.64E-05	2.07E-04	0.333				
	1	-9.41E-06	1.06E-04					
	2	9.66E-05	2.14E-04					
	3	2.81E-05	1.64E-04					
	4	-7.61E-06	7.48E-05					
Jerk mean Acc y	0	1.47E-04	5.08E-04	0.144				
	1	5.69E-05	2.54E-04					
	2	-8.60E-05	3.71E-04					
	3	-3.25E-08	4.06E-04					
	4	2.35E-04	3.59E-04					
Jerk mean Acc z	0	1.66E-05	4.37E-04	0.003	1.000	0.106	0.186	1.000
	1	-1.73E-06	2.71E-04			0.070	0.125	1.000
	2	-3.51E-04	2.39E-04				1.000	0.045
	3	-3.53E-04	4.07E-04					0.083
	4	-1.33E-05	2.20E-04					
Jerk std Acc x	0	0.704	0.195	0.000	1.000	0.276	1.000	0.008
	1	0.680	0.163			0.294	1.000	0.009
	2	0.517	0.099				0.094	1.000
	3	0.832	0.414					0.002
	4	0.443	0.154					
Jerk std Acc y	0	0.704	0.305	0.000	1.000	1.000	1.000	0.001
	1	0.647	0.194			1.000	1.000	0.001
	2	0.516	0.114				1.000	0.123
	3	0.575	0.263					0.073
	4	0.359	0.132					
Jerk std Acc z	0	0.891	0.358	0.000	1.000	0.510	1.000	0.001
	1	0.903	0.343			0.334	0.717	0.000
	2	0.632	0.222				1.000	0.435
	3	0.740	0.391					0.190
	4	0.455	0.148					

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Table 17 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RMS Acc x	0	9.837	0.246	0.021	1.000	1.000	1.000	0.148
	1	9.777	0.109			1.000	1.000	1.000
	2	9.853	0.077				0.444	0.019
	3	9.741	0.183					1.000
	4	9.647	0.209					
RMS Acc y	0	1.628	0.583	0.001	1.000	1.000	0.106	0.771
	1	1.621	0.576			0.844	0.264	1.000
	2	1.343	0.194				0.001	0.016
	3	2.001	0.269					1.000
	4	1.958	0.566					
RMS Acc z	0	2.512	1.283	0.409				
	1	2.354	0.550					
	2	2.068	0.213					
	3	2.561	1.047					
	4	2.613	0.937					
RMS Gyr x	0	26.126	4.905	0.000	0.490	0.002	0.000	0.000
	1	14.045	12.883			0.844	0.203	0.032
	2	9.477	11.876				1.000	1.000
	3	7.554	9.326					1.000
	4	4.274	8.073					
RMS Gyr y	0	17.974	8.081	0.000	0.212	0.045	0.065	0.000
	1	10.424	10.708			1.000	1.000	0.049
	2	7.584	9.212				1.000	0.227
	3	4.760	5.441					0.166
	4	1.697	2.993					
RMS Gyr z	0	18.572	3.769	0.000	0.282	0.002	0.000	0.000
	1	9.446	8.945			1.000	0.128	0.004
	2	5.457	6.587				1.000	0.480
	3	3.100	3.593					1.000
	4	2.479	4.714					
RoM Acc x	0	12.516	3.594	0.000	1.000	0.751	1.000	0.002
	1	11.168	1.794			1.000	1.000	0.012
	2	10.162	1.673				0.196	0.520
	3	12.779	3.692					0.000
	4	8.485	1.504					

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Table 17 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
RoM Acc y	**0**	11.026	5.782	0.004	1.000	1.000	1.000	0.401
	1	11.543	3.812			1.000	1.000	0.004
	2	9.311	2.281				1.000	0.351
	3	11.166	3.429					0.012
	4	7.442	1.734					
RoM Acc z	**0**	12.859	5.048	0.000	1.000	0.551	1.000	0.001
	1	14.332	5.775			0.073	0.875	0.000
	2	10.053	3.908				1.000	0.595
	3	10.873	3.382					0.043
	4	7.225	2.157					
RoM Gyr x	**0**	148.557	43.080	0.000	0.572	0.002	0.010	0.000
	1	77.261	71.518			0.678	1.000	0.048
	2	52.565	66.600				1.000	1.000
	3	54.719	66.725					1.000
	4	22.741	42.553					
RoM Gyr y	**0**	120.704	64.216	0.000	0.248	0.018	0.410	0.000
	1	81.124	86.317			1.000	1.000	0.178
	2	48.290	61.923				1.000	1.000
	3	44.313	55.018					0.101
	4	10.777	18.390					
RoM Gyr z	**0**	115.454	31.289	0.000	0.785	0.022	0.000	0.000
	1	70.307	65.355			1.000	0.123	0.001
	2	37.587	45.605				1.000	0.092
	3	22.769	26.844					1.000
	4	15.317	28.996					
Pitch mean	**0**	0.222	1.216	0.053				
	1	0.670	2.252					
	2	1.347	1.669					
	3	2.635	2.968					
	4	0.792	1.745					
Pitch std	**0**	1.979	0.201	0.006	1.000	0.829	0.730	1.000
	1	1.852	0.439			1.000	0.111	1.000
	2	1.787	0.163				0.004	0.194
	3	2.384	0.902					1.000
	4	2.053	0.335					

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Table 17 – *Continued from previous page*

Metric	Pull Test score	Mean	Std. Deviation	Kruskal Wallis (sig)	Pairwise Comparison (Adj. sig)			
					1	2	3	4
Roll mean	**0**	0.768	0.955	0.001	0.155	0.008	0.462	1.000
	1	-0.275	1.128			1.000	1.000	0.178
	2	-0.464	0.673				1.000	0.009
	3	-0.111	0.964					0.520
	4	0.803	1.777					
Roll std	**0**	2.285	0.365	0.000	0.444	0.001	0.000	0.002
	1	1.898	0.421			0.444	0.040	0.844
	2	1.576	0.242				1.000	1.000
	3	1.392	0.424					1.000
	4	1.552	0.417					

B.1.2 PD patients vs HC

Table 18: Results of the Kruskal-Wallis test for all the activities, highlighting the metrics with a value smaller than 0.05.

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
Duration of the activity									
Jerk mean in Acc_x									
Jerk mean in Acc_y									
Jerk mean in Acc_z									
Jerk std in Acc_x									
Jerk std in Acc_y									
Jerk std in Acc_z									
RMS Acc_x									
RMS Acc_y									
RMS Acc_z									
RMS Gyr_x									
RMS Gyr_y									
RMS Gyr_z									
RoM Acc_x									
RoM Acc_y									
RoM Acc_z									
RoM Gyr_x									
RoM Gyr_y									
RoM Gyr_z									
Pitch mean									
Pitch std									
Roll mean									
Roll std									

B.1.3 H&Y score

Table 19: Results of the Kruskal-Wallis test for all the activities, highlighting the metrics with a value smaller than 0.05.

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
Duration of the activity									
Jerk mean in Acc_x									
Jerk mean in Acc_y									
Jerk mean in Acc_z									
Jerk std in Acc_x									
Jerk std in Acc_y									
Jerk std in Acc_z									
RMS Acc_x									
RMS Acc_y									
RMS Acc_z									
RMS Gyr_x									
RMS Gyr_y									
RMS Gyr_z									
RoM Acc_x									
RoM Acc_y									
RoM Acc_z									
RoM Gyr_x									
RoM Gyr_y									
RoM Gyr_z									
Pitch mean									
Pitch std									
Roll mean									
Roll std									

B.1.4 UPDRS-III score

Table 20: Results of the Kruskal-Wallis test for all the activities, highlighting the metrics with a value smaller than 0.05.

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
Duration of the activity									
Jerk mean in Acc_x									
Jerk mean in Acc_y									
Jerk mean in Acc_z									
Jerk std in Acc_x									
Jerk std in Acc_y									
Jerk std in Acc_z									
RMS Acc_x									
RMS Acc_y									
RMS Acc_z									
RMS Gyr_x									
RMS Gyr_y									
RMS Gyr_z									
RoM Acc_x									
RoM Acc_y									
RoM Acc_z									
RoM Gyr_x									
RoM Gyr_y									
RoM Gyr_z									
Pitch mean									
Pitch std									
Roll mean									
Roll std									

B.2 Pearson product-moment correlation

B.2.1 Pull test score

Table 21: Pearson product-moment correlation (with a 95% confidence interval for each correlation coefficient) between the selected features of each task and the pull test score.

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
Activity Duration	-0.031	0.340	0.223	0.431	0.463	0.570	0.585	0.611	0.613
Jerk mean Acc x	0.487	0.314	-0.285	-0.299	0.263	-0.150	-0.555	-0.048	-0.113
Jerk mean Acc y	-0.208	-0.290	0.219	0.204	-0.199	-0.196	-0.194	-0.011	0.043
Jerk mean Acc z	0.275	0.121	-0.089	-0.115	0.133	-0.027	-0.056	-0.009	-0.161
Jerk std Acc x	0.216	0.221	0.373	0.167	0.096	-0.187	-0.305	-0.162	-0.198
Jerk std Acc y	0.017	0.064	0.253	-0.090	0.078	-0.449	-0.533	-0.410	-0.451
Jerk std Acc z	0.106	0.016	0.314	-0.030	0.029	-0.428	-0.492	-0.406	-0.430
RMS Acc x	-0.370	-0.246	-0.089	0.241	-0.032	-0.310	-0.411	-0.309	-0.317
RMS Acc y	0.245	0.241	0.116	-0.355	-0.135	0.329	0.226	0.314	0.286
RMS Acc z	0.310	0.335	0.377	0.313	0.303	0.184	0.047	0.074	0.066
RMS Gyr x	-0.382	-0.153	-0.227	-0.525	-0.545	-0.538	-0.635	-0.566	-0.583
RMS Gyr y	-0.111	-0.461	-0.412	-0.629	-0.579	-0.561	-0.572	-0.579	-0.578
RMS Gyr z	-0.359	-0.317	-0.329	-0.682	-0.708	-0.658	-0.663	-0.658	-0.665
RoM Acc x	0.132	-0.011	-0.022	0.142	-0.035	-0.267	-0.278	-0.245	-0.304
RoM Acc y	0.079	0.081	0.040	-0.414	-0.338	-0.338	-0.363	-0.285	-0.275
RoM Acc z	0.065	0.110	0.204	0.087	-0.106	-0.397	-0.411	-0.418	-0.436
RoM Gyr x	-0.368	-0.154	-0.260	-0.511	-0.510	-0.515	-0.611	-0.533	-0.543
RoM Gyr y	-0.112	-0.447	-0.429	-0.539	-0.521	-0.531	-0.512	-0.540	-0.519
RoM Gyr z	-0.382	-0.340	-0.328	-0.586	-0.632	-0.626	-0.609	-0.634	-0.638
Pitch mean	-0.262	-0.044	0.162	-0.140	0.138	0.233	0.234	0.180	0.204
Pitch std	0.428	0.191	0.130	0.160	0.094	0.121	0.179	0.146	0.187

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Table 21 – *Continued from previous page*

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
Roll mean	0.079	-0.206	0.130	0.309	-0.368	-0.146	-0.084	0.017	0.027
Roll std	-0.054	0.417	0.052	-0.182	-0.251	-0.188	-0.600	-0.610	-0.574

B.2.2 PD patients vs HC

Table 22: Pearson product-moment correlation (with a 95% confidence interval for each correlation coefficient) between the selected features of each task and the diagnosis of PD.

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
Activity Duration	-0.219	-0.486	-0.350	-0.379	-0.466	-0.339	-0.338	-0.505	-0.471
Jerk mean Acc x	0.017	0.026	0.101	0.589	-0.633	0.179	0.420	0.286	-0.026
Jerk mean Acc y	-0.167	0.140	-0.030	-0.087	0.072	0.264	0.205	0.197	-0.016
Jerk mean Acc z	-0.118	0.316	-0.132	0.147	-0.156	-0.073	-0.329	-0.042	0.028
Jerk std Acc x	0.198	0.354	0.052	0.461	0.414	0.415	0.495	0.372	0.371
Jerk std Acc y	0.266	0.139	-0.069	0.472	0.268	0.605	0.628	0.555	0.534
Jerk std Acc z	0.115	0.388	0.097	0.457	0.464	0.509	0.562	0.487	0.465
RMS Acc x	0.257	0.223	0.158	-0.179	-0.266	0.362	0.500	0.321	0.282
RMS Acc y	0.280	-0.142	-0.094	0.215	0.263	0.145	0.334	0.159	0.163
RMS Acc z	0.080	0.061	-0.088	-0.013	0.052	0.106	0.354	0.240	0.261
RMS Gyr x	0.326	0.109	0.249	0.455	0.466	0.363	0.341	0.373	0.386
RMS Gyr y	0.075	0.417	0.315	0.431	0.473	0.429	0.439	0.431	0.456
RMS Gyr z	0.311	0.194	0.268	0.354	0.443	0.306	0.295	0.314	0.316
RoM Acc x	0.107	0.315	0.137	0.425	0.576	0.542	0.561	0.453	0.453
RoM Acc y	0.189	-0.102	-0.075	0.453	0.424	0.654	0.702	0.581	0.451
RoM Acc z	0.102	0.258	0.181	0.335	0.512	0.540	0.628	0.535	0.448

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Table 22 – *Continued from previous page*

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
RoM Gyr x	0.283	0.058	0.168	0.408	0.415	0.422	0.350	0.405	0.388
RoM Gyr y	0.054	0.387	0.319	0.349	0.489	0.435	0.440	0.414	0.429
RoM Gyr z	0.277	0.167	0.212	0.289	0.343	0.355	0.364	0.358	0.328
Pitch mean	0.103	0.020	-0.032	-0.165	0.237	-0.380	-0.269	-0.465	-0.418
Pitch std	-0.386	0.140	-0.018	0.288	0.455	0.100	0.254	0.126	0.225
Roll mean	-0.044	0.309	-0.051	0.052	0.003	0.268	0.465	0.182	0.114
Roll std	0.427	-0.221	-0.074	0.346	0.484	0.323	0.425	0.499	0.524

B.2.3 H&Y score

Table 23: Pearson product-moment correlation (with a 95% confidence interval for each correlation coefficient) between the selected features of each task and the H&Y score.

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
Activity Duration	-0.144	0.321	0.171	0.454	0.362	0.678	0.651	0.693	0.704
Jerk mean Acc x	0.331	0.520	-0.412	-0.215	0.136	-0.089	-0.382	-0.028	0.015
Jerk mean Acc y	-0.106	-0.474	0.297	0.067	-0.083	0.008	0.057	0.225	0.123
Jerk mean Acc z	0.340	0.121	-0.060	-0.264	0.171	0.284	0.323	0.322	0.257
Jerk std Acc x	0.487	0.079	0.248	0.113	0.027	-0.174	-0.245	-0.185	-0.218
Jerk std Acc y	0.393	0.035	0.242	-0.060	0.045	-0.294	-0.386	-0.394	-0.371
Jerk std Acc z	0.327	-0.011	0.274	0.087	0.015	-0.207	-0.271	-0.291	-0.308
RMS Acc x	-0.363	-0.138	0.014	0.417	0.070	-0.310	-0.446	-0.356	-0.403
RMS Acc y	0.526	0.427	0.166	-0.516	-0.263	0.523	0.462	0.526	0.478
RMS Acc z	0.539	0.454	0.581	0.470	0.559	0.505	0.553	0.529	0.527
RMS Gyr x	-0.002	0.076	-0.015	-0.194	-0.229	-0.372	-0.485	-0.401	-0.414

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Table 23 – *Continued from previous page*

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
RMS Gyr y	0.148	-0.218	-0.215	-0.354	-0.359	-0.374	-0.384	-0.438	-0.438
RMS Gyr z	-0.011	-0.013	-0.059	-0.475	-0.522	-0.486	-0.500	-0.501	-0.502
RoM Acc x	0.359	-0.070	-0.044	0.205	-0.041	-0.118	-0.015	-0.191	-0.259
RoM Acc y	0.315	0.106	0.065	-0.306	-0.317	-0.047	0.076	-0.135	-0.015
RoM Acc z	0.251	0.074	0.312	0.177	0.003	-0.125	-0.012	-0.219	-0.172
RoM Gyr x	0.088	0.036	-0.042	-0.202	-0.218	-0.282	-0.435	-0.316	-0.342
RoM Gyr y	0.142	-0.212	-0.231	-0.244	-0.323	-0.276	-0.243	-0.342	-0.280
RoM Gyr z	-0.069	-0.058	-0.074	-0.388	-0.451	-0.445	-0.437	-0.460	-0.487
Pitch mean	-0.257	0.059	0.100	-0.131	0.175	-0.088	-0.059	-0.114	-0.038
Pitch std	0.391	0.178	0.103	0.112	0.147	0.196	0.257	0.249	0.198
Roll mean	-0.180	-0.274	0.116	0.125	-0.177	0.070	-0.030	0.082	0.169
Roll std	0.087	0.537	0.036	-0.286	-0.274	-0.303	-0.589	-0.636	-0.482

B.2.4 UPDRS-III score

Table 24: Pearson product-moment correlation (with a 95% confidence interval for each correlation coefficient) between the selected features of each task and the UPDRS-III score.

Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
Activity Duration	-0.109	0.236	0.339	0.378	0.339	0.518	0.611	0.583	0.575
Jerk mean Acc x	0.236	0.300	0.049	-0.172	0.049	-0.187	-0.286	-0.065	-0.061
Jerk mean Acc y	0.096	-0.420	-0.119	0.076	-0.119	-0.013	-0.040	0.287	0.232
Jerk mean Acc z	0.178	0.033	0.216	-0.230	0.216	0.192	0.187	0.207	0.069
Jerk std Acc x	0.502	0.125	0.273	0.335	0.273	-0.004	-0.110	-0.018	-0.047
Jerk std Acc y	0.248	0.032	0.290	0.175	0.290	-0.222	-0.324	-0.249	-0.241

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Metric	Pull Test	Sitting	Sit Get Up	Lie On Bed	Get Up Bed	Walk	180 Turning	Right Turning	Left Turning
Jerk std Acc z	0.388	-0.032	0.269	0.252	0.269	-0.111	-0.192	-0.155	-0.164
RMS Acc x	-0.106	-0.017	-0.024	0.207	-0.024	-0.209	-0.365	-0.282	-0.308
RMS Acc y	0.435	0.423	-0.166	-0.356	-0.166	0.592	0.525	0.583	0.551
RMS Acc z	0.360	0.219	0.501	0.494	0.501	0.481	0.561	0.553	0.547
RMS Gyr x	-0.018	0.026	-0.271	-0.250	-0.271	-0.361	-0.464	-0.389	-0.398
RMS Gyr y	0.114	-0.253	-0.374	-0.374	-0.374	-0.370	-0.377	-0.417	-0.412
RMS Gyr z	-0.009	-0.061	-0.496	-0.456	-0.496	-0.449	-0.460	-0.457	-0.461
RoM Acc x	0.352	-0.143	0.285	0.381	0.285	-0.018	0.005	-0.061	-0.147
RoM Acc y	0.117	0.067	-0.164	-0.244	-0.164	-0.031	-0.019	-0.072	-0.036
RoM Acc z	0.299	0.009	0.059	0.268	0.059	-0.122	-0.018	-0.198	-0.175
RoM Gyr x	0.074	-0.013	-0.257	-0.242	-0.257	-0.290	-0.426	-0.324	-0.336
RoM Gyr y	0.125	-0.245	-0.344	-0.258	-0.344	-0.296	-0.261	-0.339	-0.279
RoM Gyr z	-0.053	-0.093	-0.428	-0.386	-0.428	-0.422	-0.426	-0.434	-0.462
Pitch mean	-0.152	0.177	0.331	-0.176	0.331	-0.037	-0.085	-0.092	0.041
Pitch std	0.207	0.076	0.340	0.304	0.340	0.214	0.420	0.335	0.202
Roll mean	-0.024	-0.121	-0.263	0.181	-0.263	0.100	0.256	0.143	0.374
Roll std	0.104	0.476	-0.094	-0.090	-0.094	-0.232	-0.481	-0.569	-0.395

B.2.5 Walking metrics

Table 25: Pearson product-moment correlation (with a 95% confidence interval for each correlation coefficient) between the selected gait features of each task and the pull test score, H&Y score, UPDRS-III score and PD diagnosis.

Metric	Pull Test Score	H&Y Score	UPDRS-III Score	PD patients vs HC
Step length	-0.534	-0.512	-0.530	0.450
Stride length	-0.518	-0.503	-0.527	0.410
Velocity	-0.613	-0.629	-0.531	0.453
Cadence	-0.281	-0.341	-0.101	0.066
Number of steps	0.621	0.677	0.613	-0.412
Step time	0.315	0.417	0.217	-0.132
Stride time	0.319	0.421	0.221	-0.062
Stance time	0.422	0.418	0.160	-0.196
Swing time	0.096	0.240	0.171	0.061
Double support phase	0.358	0.249	0.130	-0.219
Stance phase	0.137	-0.019	-0.078	-0.129
Swing phase	-0.092	0.053	0.079	0.161
AS step length	-0.009	-0.089	-0.143	-0.038
AS step time	0.187	0.260	0.240	-0.180
AS velocity	0.041	0.026	-0.050	-0.048
AS stance time	0.100	0.213	0.196	-0.071
AS swing time	0.105	0.207	0.200	0.037
SD step length	0.124	0.204	0.160	0.256
SD step time	0.123	0.231	0.216	-0.088
SD step velocity	0.102	0.169	0.151	0.285
SD stance time	0.112	0.223	0.205	-0.072
SD swing time	0.107	0.217	0.207	0.031

B.3 Multiple Linear Regression

Table 26: Multiple linear regression between the features of each activity and the pull test score, H&Y score, UPDRS-III score and PD diagnosis.

	Pull Test Score			H&Y Score			UPDRS-III Score			PD patients vs HC		
Activity	**Variables in the model**	**Adj. R squared**	**ANOVA sig**	**Variables in the model**	**Adj. R squared**	**ANOVA sig**	**Variables in the model**	**Adj. R squared**	**ANOVA sig**	**Variables in the model**	**Adj. R squared**	**ANOVA sig**
Pull Test	Jerk mean Acc x	0.204	0.014	RMS Acc z	0.257	0.008	Jerk std Acc x	0.252	0.015	Roll std Pitch std Activity Duration	0.419	0.000
Sitting	RMS Gyr y Roll std Pitch std Jerk mean Acc y	0.513	0.000	Roll std Jerk mean Acc x Jerk mean Acc y Roll mean	0.554	0.000	Roll std RoM Gyr y RMS Acc y RoM Acc y Roll mean Jerk mean Acc y Pitch mean RMS Acc z	0.652	0.000	Activity Duration RMS Gyr y Jerk std Acc x	0.475	0.000
Sit Get Up	RoM Gyr y RMS Acc z RMS Gyr x	0.331	0.000	RMS Acc z RMS Acc x RMS Acc y	0.486	0.000	RMS Acc z	0.123	0.002	Activity Duration RoM Gyr y Pitch mean Jerk mean Acc z RoM Acc z	0.356	0.000

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	Pull Test Score			H&Y Score			UPDRS-III Score			PD patients vs HC		
Activity	**Variables in the model**	**Adj. R squared**	**ANOVA sig**	**Variables in the model**	**Adj. R squared**	**ANOVA sig**	**Variables in the model**	**Adj. R squared**	**ANOVA sig**	**Variables in the model**	**Adj. R squared**	**ANOVA sig**
Lie On Bed	RMS Gyr y RMS Acc z Roll mean RoM Gyr y RoM Gyr x Jerk mean Acc z RMS Gyr x	0.709	0.000	RMS Gyr z RMS Acc z RMS Acc x RoM Acc x RMS Gyr x RoM Acc z Pitch mean RoM Gyr x	0.756	0.000	RMS Acc z RMS Gyr z RoM Acc x Jerk mean Acc z	0.600	0.000	Jerk mean Acc x RMS Gyr x Jerk std Acc x RoM Gyr z RMS Gyr y Pitch std Pitch mean	0.755	0.000
Get Up Bed	RMS Gyr y Pitch mean RMS Acc z Jerk mean Acc z RoM Gyr y RoM Acc z	0.689	0.000	RMS Acc z RMS Gyr z RMS Gyr x Jerk mean Acc z Jerk mean Acc x Jerk mean Acc y	0.693	0.000	RMS Acc z RMS Gyr z Pitch mean Jerk std Acc y RoM Acc z	0.677	0.000	Jerk mean Acc x RoM Gyr y Jerk std Acc x Jerk std Acc y RoM Acc z RoM Gyr z RMS Gyr y RoM Acc x Activity Duration	0.732	0.000
Walk	RMS Gyr z RMS Acc z RoM Acc z Step length	0.705	0.000	Activity Duration RMS Acc z Roll std Stance time Stride length RMS Acc y RMS Acc x	0.781	0.000	RMS Acc y Stride length RoM Acc z AS velocity RoM Acc y RMS Acc z RMS Acc x Pitch mean Jerk mean Acc z	0.828	0.000	RoM Acc y RoM Acc x Roll mean Pitch mean Cadence Roll std	0.579	0.000

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Table 26 – *Continued from previous page*

	Pull Test Score			H&Y Score			UPDRS-III Score			PD patients vs HC		
Activity	**Variables in the model**	**Adj. R squared**	**ANOVA sig**	**Variables in the model**	**Adj. R squared**	**ANOVA sig**	**Variables in the model**	**Adj. R squared**	**ANOVA sig**	**Variables in the model**	**Adj. R squared**	**ANOVA sig**
180 Turning	RMS Gyr z Activity Duration	0.566	0.000	Activity Duration RMS Acc z Jerk mean Acc x	0.610	0.000	Activity Duration RMS Acc z Roll mean Pitch std RoM Acc z	0.768	0.000	RoM Acc y Jerk mean Acc y	0.541	0.000
Right Turning	RMS Gyr z Activity Duration RMS Acc y RoM Acc z Jerk std Acc z	0.665	0.000	Activity Duration RMS Acc z RMS Gyr z Jerk mean Acc z RMS Acc y	0.711	0.000	Activity Duration RMS Acc z RMS Acc y RoM Acc z Jerk std Acc z Jerk std Acc y Pitch std	0.760	0.000	Pitch mean Activity Duration RMS Acc z Jerk mean Acc x RoM Gyr x RMS Gyr z RoM Gyr z	0.665	0.000
Left Turning	RMS Gyr z Activity Duration	0.600	0.000	Activity Duration RMS Acc z RMS Gyr z	0.666	0.000	Activity Duration RMS Acc z Roll mean RoM Gyr y RMS Acc y Jerk mean Acc y	0.671	0.000	Jerk std Acc y Pitch mean RMS Gyr z RMS Gyr x	0.504	0.000