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On the Reliability of Wearable Sensors for Assessing Movement Disorder-Related Gait Quality and Imbalance: A Case Study of Multiple Sclerosis

Steven Díaz Hernández
University of South Florida

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On the Reliability of Wearable Sensors for Assessing Movement Disorder-Related Gait Quality and Imbalance: A Case Study of Multiple Sclerosis

by

Steven Díaz Hernández

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
Department of Computer Science and Engineering
College of Engineering
University of South Florida

Major Professor: Tempe Ge Neal, Ph.D.
Paul Rosen, Ph.D.
Sudeep Sarkar, Ph.D.
Sean Barbeau, Ph.D.
Jeannie B. Stephenson, Ph.D.

Date of Approval:
March 4, 2022

Keywords: Gait Analysis, Movement Disorder, Walking Quality, Sensor Reliability

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Dedication

To my amazing wife, my mother, my father, my siblings, and my friends. Thank you all for your support and for always believing in me.

A special dedication to Dr. Miguel Labrador. Thank you for the support and guidance for most of my journey. All your life and professional advice will never be forgotten. Rest in peace.
Acknowledgments

I would like to thank Dr. Tempebt Neal for her invaluable guidance and support throughout my last year of this work. I would also like to thank Dr. Jeannie B. Stephenson; besides not having the official title, she has been a great advisor during the development of this work. I would further like to thank my graduate committee members, Dr. Paul Rosen, Dr. Sudeep Sarkar, and Dr. Sean Barbeau, for taking the time to be part of my committee. I would also like to thank my friends, Jennifer Adorno, Mark DiSano, Dr. Yueng De La Hoz and Dr. Shamaria Engram, for their support and for all of the great experiences we have shared over the past years.

Finally, I would like to thank the National Science Foundation’s Florida-Georgia Louis Stokes Alliance for Minority Participation Bridge to the Doctorate under Grant No. 1400837, and the National Science Foundation under grants No. 1458928 and 1645025, An REU Site on Ubiquitous Sensing.
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Approximately 33 million American adults had a movement disorder associated with medication use, ear infections, injury, or neurological disorders in 2008, with over 18 million people affected by neurological disorders worldwide. Physical therapists assist people with movement disorders by providing interventions to reduce pain, improve mobility, avoid surgeries, and prevent falls and secondary complications of neurodegenerative disorders. Current gait assessments used by physical therapists, such as the Multiple Sclerosis Walking Scale, provide only semi-quantitative data, and cannot assess walking quality in detail or describe how one’s walking quality changes over time. As a result, quantitative systems have grown as useful tools for measuring and evaluating movement disorders, particularly to track an individual’s gait.

A variety of quantitative systems are used to analyze the spatiotemporal parameters of gait. These include video motion capture systems, walkway systems with embedded pressure activated sensors, and body worn inertial sensors. Since walkway systems and video motion capture systems are limited to clinic or research settings and cannot gather data in the individual’s natural setting, body worn and handheld inertial sensors are increasingly favored by researchers, clinicians, and patients themselves to assess daily step activity. Similarly, in this dissertation, we evaluate wearable sensor-based methodologies to assess gait quality and balance, particularly in individuals diagnosed with Multiple Sclerosis (MS).

This dissertation consists of three key research objectives. First, we investigate performance, step count and segmentation differences between movement-capturing sensors embedded in smartphones and standalone, wearable inertial measurement units (wIMUs) for gait assessment. We, then, propose novel methods to estimate step length and width and
for processing raw signals gathered from wIMUs. Finally, we demonstrate the reliability of wIMUs for gait analysis in MS against a gold standard walkway system.

Our methodology takes advantage of signal processing and machine learning techniques for analyzing wIMUs’ signals and converting these raw signals into practical significance. Using the intra-class correlation coefficient (ICC) to measure consistency, and the mean difference to measure the between-method difference of our proposed methods with existing methods in wIMU software algorithms, the proposed methods showed excellent consistency (ICC > 0.98) when measuring multiple gait spatiotemporal parameters, such as step time, cadence, gait velocity, and step length. We also show that the consistency of gait measurement by wIMUs during both comfortable and fast speed trials were not affected by MS, asserting the use of wearable devices in clinical trials.
Chapter 1: Introduction

Gait, balance, and joint kinematics in people with movement disorders are prominent research topics. Movement disorders may result from complications occurring in the musculoskeletal system (e.g., [140]), neurological system (e.g., [143]), or other body systems, leading to dire living conditions. In the last decade alone, the number of total knee replacements in the United States increased by approximately 616,000 cases; the demand for replacement procedures is predicted to increase to approximately 3.48 million by the year 2030 [18, 85]. Similarly, 1.6 million Americans underwent a limb amputation in 2005, with an expected increase to 3.6 million by 2050 [167]. Moreover, about 33 million American adults faced balance problems caused by medications, ear infections, injuries, or neurological disorders in 2008 [3]. Some of the common neurological disorders that cause gait and balance problems are stroke (i.e., reduced blood flow to the brain, resulting in potential brain damage), Alzheimer’s disease (AD) (i.e., a progressive disease resulting in memory loss and confusion), Parkinson’s disease (PD) (i.e., a neurological movement disorder commonly associated with tremors), Multiple Sclerosis (MS) (i.e., a disease wherein the immune systems attacks the nervous system), and ataxia (i.e., lack of muscle or voluntary movement control). More than 18 million people are affected by these neurological disorders worldwide [2, 4, 102, 6].

Physical therapists aim to help individuals with movement disorders by providing interventions to reduce pain; increase range of motion and muscle strength; improve balance; improve gait and mobility; and prevent falls [1]. Physical therapists often evaluate their rehabilitation outcomes in a subjective manner, such as through visual observation, clinical impressions, and through other tests or measures. Meanwhile, researchers have developed applications to assess rehabilitation outcomes, specifically concerning measurement of gait.
and walking imbalance, using novel technologies such as external sensors, smartphones, and wearable sensors. The performance of such systems depend entirely on the interaction of the patient with the sensor used; external sensors are deployed in the environment around the patient, while smartphones and wearable sensors are mounted on the patient [87].

Common external sensors are camera-based, floor-based sensors, or force platforms. A camera-based system can either use one or multiple cameras placed at points of interest around the environment where the patient will perform some specified exercise or activity, like walking or turning. Camera-based systems have been used primarily to conduct motion analysis in research labs, but recently, camera systems have been deployed in people’s homes to track their daily activities or assess their fall risk [45, 119]. On the other hand, sensors used in floor-based systems are placed in floor mats to measure force and pressure as the patient walks on them [112]. Force platform-based systems, similar to floor-based systems, use force and pressure while a person is standing on the platform to measure postural stability or gait.

Unlike external sensors, wearable sensors are cheaper and are typically mounted to the subject’s body, eliminating cost and portability limitations set by external sensors [37]. The high level of portability allows physical therapists and researchers to analyze gait and balance not only in research laboratories, but also in clinics, in patients’ homes, or out in the community. The accuracy of a wearable sensor system at measuring gait and imbalance depends on how many sensors are used, where and how are the sensors located, and other challenges that will be further discussed. There are many types of wearable sensors that are used in applications, ranging from monitoring subjects’ physiologic responses like heart rate, electrocardiogram (ECG), or blood glucose levels [119], to measuring gait, balance, and range of motion (RoM) during movements, like walking, turning, sit to stand, or postural sway. Wearable sensors have been utilized in conjunction with tests and measures, like the Timed Up and Go Test [126, 138], a test of mobility and fall risk in older adults, to provide more detailed and objective balance data [67]. Wearable sensors have also been used to
study changes in gait and balance over time in people with neurodegenerative diseases, and to investigate improvements post interventions [101].

1.1 Problem Statement

Floor-based sensors and force platform systems are used in research labs or clinically to provide very detailed spatiotemporal gait variables and postural stability measurements, respectively. However, the main drawbacks of these systems are their cost and lack of portability; they are primarily confined to research labs and are rarely available for use in clinical settings. Additionally, camera-based systems are unable to track a subject outside of the camera’s visibility, leading to purchasing additional sensors to increase the system’s range of visibility, thus increasing the cost of the overall system [87, 37]. In addition, camera-based systems are computationally expensive to obtain accurate results and may raise privacy concerns. As such, we investigate the use of wearable devices to assess gait and balance, leveraging accelerometer and gyroscope sensors embedded in wearable devices. Inertial measurement units (IMUs), which are derived from a combination of movement-tracking sensors like the accelerometer and gyroscope, are used in this work to capture the movement of specific locations of a human body (feet, thigh, chest, lower back, etc.). This movement is captured as a three dimensional raw signal from each IMU sensor, in which all signals of each sensor are analyzed and processed to extract gait spatiotemporal parameters. Signal processing techniques and machine learning are also utilized to make sense of the raw IMU data. This work consists of three key studies:

1. a case study that compares the accuracy and reliability between smartphones and inertial measurement units when assessing gait,

2. a study that proposes new methods to estimate step length and step width using wearable sensors, and
3. a study that proposes new methods to process raw IMU signals. This study also assesses wearable sensor’s reliability to measure gait given a set of patients diagnosed with Multiple Sclerosis.

This research explores several challenges related to wearable sensor-based gait analysis, including:

- **Efficiency**: A wearable sensor-based gait analysis system must be efficient and well-developed to support individuals with neurological disorders as assessed in this dissertation, particularly to affect clinical recommendations and outcomes.

- **Generalization**: A wearable sensor-based gait analysis system must adapt to the complexity of IMU signals from different patients with varying symptoms.

- **Data Pre-Processing**: A wearable sensor-based gait analysis system must adequately involve data cleaning processes to properly denoise IMU signals, account for sensor alignment, and enable signal fusion.

### 1.2 Contributions

The main contributions of this dissertation are presented below. Each contribution will be further explained in the subsequent chapters. Specifically, this research

- introduces a two-level taxonomy (performed analysis and parameters’ categories) to describe gait and balance analyses,

- compares the performance between smartphone and inertial measurement units using a previously proposed gait methodology,

- describes how neural network topologies can be used to extract gait spatiotemporal parameters, such as step length,

- describes an initial approach to extract one of the most difficult gait parameters to be extracted with wearable sensors, i.e., step width,
• describes a novel way to process raw signals from wearable IMU sensors to extract gait parameters, and

• assesses the reliability of wearable IMU sensors to measure gait in Multiple Sclerosis against a gold standard system.

1.3 Structure of the Dissertation

This dissertation is structured as follows. Chapter 2 contains the literature review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement, presenting the common sensors used in this topic and their design issues. It also introduces a taxonomy based on the different parameters that can be used to assess gait and balance. Chapter 3 presents the case study that investigates the differences between smartphones and inertial measurement units when assessing gait. Chapter 4 presents the study that proposes new methods to estimate step length and step width using wearable sensors. Chapter 5 presents a study that proposes new methods to process raw signals. It also assesses wearable sensor’s reliability to measure gait and evaluates the final methodology used in this work. Finally, Chapter 6 concludes the dissertation and presents possible future research.
Chapter 2: Literature Review

This chapter surveys the state-of-the-art in wearable sensor technology in gait, balance, and RoM research\(^1\). This chapter serves as a point of reference for this work, describing the existing solutions and challenges in the field. A two-level taxonomy of rehabilitation assessment is introduced, along with evaluation metrics and common algorithms used in wearable sensor technology [42].

2.1 Review Method

This literature review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [111].

2.1.1 Literature Search Strategy

PubMed, Scopus, and IEEE Xplore were used to identify articles that use wearable sensor technology to measure and/or analyze gait, balance, and/or range of motion. The following keywords were used to search within title, abstract, and/or articles’ keywords: “gait”, “balance”, “wearable sensor”, “wearable device”, “IMU”, “EMG”, “smartphone”, “accelerometer”, “gait variability”, “inertial sensor”, “postural sway”, “range of motion”, “gait analysis”, “insole sensor”, and their combinations.

2.1.2 Study Selection: Inclusion Criteria and Quality Assessment

Articles were screened by their title and abstract after they were identified through electronic databases. Articles were included if they were written in English. Articles were excluded if they did not use any type of body worn wearable sensors to measure gait, balance, and/or RoM, were published before January 2009, were conference abstracts, review articles, or case studies.

A quality assessment was performed for each of the included studies independently (Table 2.1). The quality assessment is based on three different sub-scales presented by Hagströmer et al.:

- **Internal Validity (IV):** addresses methodological bias,
- **External Validity (EV):** addresses the extent that the findings can be generalized to the population based on the study subjects, and
- **Quality of the Reported Data (QV):** assesses if the information provided is sufficient and unbiased [64].

The quality assessment checklist used in this review is based on the 15-item checklist proposed by Ghislieri et al., which is similar to those commonly used in the literature for systematic reviews [64, 55, 99, 12, 145]. The score, or number of “Yes”s, was calculated for each article. Articles were classified based on the score obtained: “high quality” if the score was greater than 10, “moderate quality” if the score was between 5 and 10, and “low quality” if the score was less than 5. Only “high quality” articles were selected for further review.
Table 2.1: Quality assessment checklist used in the literature review.

<table>
<thead>
<tr>
<th>Item</th>
<th>Criteria</th>
<th>Validity Type</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The purpose of the study is clearly stated.</td>
<td>IV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>2</td>
<td>The research question is relevant to the purpose of the study.</td>
<td>EV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>3</td>
<td>Inclusion and/or exclusion criteria are described.</td>
<td>EV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>4</td>
<td>Data collection clearly described.</td>
<td>IV/EV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>5</td>
<td>Same data collection procedure for all subjects.</td>
<td>EV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>6</td>
<td>Reliable data processing clearly described.</td>
<td>IV/EV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>7</td>
<td>Data loss &lt; 20%.</td>
<td>EV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>8</td>
<td>Outcomes are relevant to the topic.</td>
<td>EV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>9</td>
<td>Outcomes are same for all subjects.</td>
<td>IV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>10</td>
<td>Scientific question stated in the aim is answered.</td>
<td>IV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>11</td>
<td>Results are clearly presented and discussed.</td>
<td>IV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>12</td>
<td>Appropriate statistical analysis techniques used.</td>
<td>QV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>13</td>
<td>Statistical test used clearly stated.</td>
<td>QV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>14</td>
<td>Analytical software used is clearly stated and referenced.</td>
<td>QV</td>
<td>Yes/No</td>
</tr>
<tr>
<td>15</td>
<td>Sufficient number of subjects.</td>
<td>QV</td>
<td>Yes/No</td>
</tr>
</tbody>
</table>
2.2 Review Results

A total of 1,677 articles were identified. After excluding 646 duplicates, 659 articles were screened based on their title and abstract, and 131 were selected for full-text assessment. Fifty-six articles were included in this systematic review after excluding articles based on the assessment results. Figure 2.1 presents the flow diagram of the study selection. Table 2.2 presents a description of the studies included, providing the reference, the year of publication, and the objective of the study. Table 2.3 presents the main characteristics of the studies included, such as parameters extracted, the population that participated in the study, sensors used, their locations, and their level of obtrusiveness.
Table 2.2: Literature on wearable sensors in gait, balance, and RoM research included in the review.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Year</th>
<th>Objective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Van den Noort et al. [151]</td>
<td>2009</td>
<td>Evaluate the use of goniometry in estimating the joint angle of the catch simultaneously with inertial sensors.</td>
</tr>
<tr>
<td>Franco et al. [51]</td>
<td>2012</td>
<td>Implement a Kalman filter using a smartphone to estimate 3-D angulation of the trunk.</td>
</tr>
<tr>
<td>Spain et al. [141]</td>
<td>2012</td>
<td>Study if wearable sensors can detect differences in balance and gait between people with MS with normal walking speeds and healthy controls.</td>
</tr>
<tr>
<td>Martori et al. [105]</td>
<td>2013</td>
<td>Develop a wearable motion analysis system to evaluate gait that consists on six IMUs.</td>
</tr>
<tr>
<td>Crea et al. [33]</td>
<td>2014</td>
<td>Describe a wearable pressure-sensitive insole sensor for lower-limb amputees feedbacks.</td>
</tr>
<tr>
<td>Hsu et al. [72]</td>
<td>2014</td>
<td>Develop gait and balance analysis algorithms to gather quantitative data considered early indicators of AD.</td>
</tr>
<tr>
<td>Patterson et al. [120]</td>
<td>2014</td>
<td>Compare a mobile technology application with a commonly used subjective balance assessment.</td>
</tr>
<tr>
<td>Tzallas et al. [150]</td>
<td>2014</td>
<td>Describe a system for continuous remote monitoring of patients with PD.</td>
</tr>
<tr>
<td>Reference</td>
<td>Year</td>
<td>Objective</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Wentick et al. [155]</td>
<td>2014</td>
<td>Investigate whether detection of gait initiation in transfemoral amputees can be useful for voluntary control of lower extremity prostheses.</td>
</tr>
<tr>
<td>Alberts et al. [11, 10]</td>
<td>2015</td>
<td>Develop a biomechanically based quantification of the BESS using inertial sensors data. Determine whether inertial data provide sufficient resolution of center of gravity movements to quantify postural stability.</td>
</tr>
<tr>
<td>Bauer et al. [16]</td>
<td>2015</td>
<td>Evaluate IMU-system when assessing movement dysfunctions of concurrent validity and reliability.</td>
</tr>
<tr>
<td>Ellis &amp; Zhu et al. [166, 46]</td>
<td>2015</td>
<td>Describe a smartphone-based application to quantify gait variability.</td>
</tr>
<tr>
<td>Godfrey et al. [57]</td>
<td>2015</td>
<td>Investigate the use of a wearable sensor compared to laboratory reference.</td>
</tr>
<tr>
<td>Jaysrichai et al. [76]</td>
<td>2015</td>
<td>Measure the knee joint angle using IMUs and reference it with a motion capture system.</td>
</tr>
<tr>
<td>Kanzler et al. [77]</td>
<td>2015</td>
<td>Present a method for calculating continuous heel and toe clearance and foot angle in the sagittal plane without knowing shoe dimensions.</td>
</tr>
<tr>
<td>Lee &amp; Kumar et al. [92, 84]</td>
<td>2015</td>
<td>Design and validate a smartphone-based system for motor assessment using IMUs.</td>
</tr>
<tr>
<td>Lin et al. [97]</td>
<td>2015</td>
<td>Present and evaluate the step count performance of a smart insole system.</td>
</tr>
</tbody>
</table>
Table 2.2: (Continued).

<table>
<thead>
<tr>
<th>Reference</th>
<th>Year</th>
<th>Objective</th>
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<tbody>
<tr>
<td>Postolache et al. [127]</td>
<td>2015</td>
<td>Develop a system to objectively record ground reaction forces, acceleration and direction of the feet using wearable sensors.</td>
</tr>
<tr>
<td>Sijobert et al. [139]</td>
<td>2015</td>
<td>Present an algorithm to estimate stride length using an accelerometer and a gyroscope.</td>
</tr>
<tr>
<td>Nouredanesh et al. [116, 115]</td>
<td>2015-16</td>
<td>Develop a method that automatically distinguishes compensatory balance responses from regular stepping pattern.</td>
</tr>
<tr>
<td>Bertolotti et al. [19]</td>
<td>2016</td>
<td>Assemble an IMU to provide measurements of limb movements and balance abilities.</td>
</tr>
<tr>
<td>Del Din et al. [36]</td>
<td>2016</td>
<td>Quantify a comprehensive range of gait parameters using a single tri-axial accelerometer. Compare gait data of older adults with PD subjects.</td>
</tr>
<tr>
<td>Horak et al. [68]</td>
<td>2016</td>
<td>Study balance and gait to represent independent domains of mobility in PD.</td>
</tr>
<tr>
<td>Lee et al. [91]</td>
<td>2016</td>
<td>Compare Multiscale Entropy (MSE) analysis of acceleration data with other features to observe falling behavior and traditional clinical scales to evaluate falling behavior.</td>
</tr>
<tr>
<td>LeMoyne et al. [93]</td>
<td>2016</td>
<td>Facilitate the acuity of the timed 25 foot walk test with the synthesis of wearable and sensors and machine learning.</td>
</tr>
<tr>
<td>Li et al. [96]</td>
<td>2016</td>
<td>Develop a sit to stand detection system to raise an alarm when an individual stand up without proper technique or assistance.</td>
</tr>
<tr>
<td>Reference</td>
<td>Year</td>
<td>Objective</td>
</tr>
<tr>
<td>----------------------------</td>
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<tr>
<td>Storm et al. [144]</td>
<td>2016</td>
<td>Evaluate accuracy of two algorithms for detection of gait events and temporal parameters during free-living walking.</td>
</tr>
<tr>
<td>Wang et al. [153]</td>
<td>2016</td>
<td>Improve autocorrelation method for gait analysis using EMG signals collected from six muscle groups of the lower limbs in hemiparetic subjects.</td>
</tr>
<tr>
<td>Iijima et al. [75]</td>
<td>2017</td>
<td>Assess quantitatively the gait disorders in the daily lives of patients with PD using with a newly developed portable gait rhythmogram.</td>
</tr>
<tr>
<td>Lebel et al. [90]</td>
<td>2017</td>
<td>Assess attitude and heading reference system at multiple segments and joints.</td>
</tr>
<tr>
<td>Robert-Lachaine et al. [130]</td>
<td>2017</td>
<td>Determine the technological error and biomechanical model differences between IMUs and an optoelectronic system.</td>
</tr>
<tr>
<td>Schlachetzki et al. [132]</td>
<td>2017</td>
<td>Develop a gait analysis system with wearable sensors to assess gait parameters in PD.</td>
</tr>
<tr>
<td>Shazad et al. [136]</td>
<td>2017</td>
<td>Provide an objective, cost-effective method to obtain balance and mobility based fall-risk in older adults.</td>
</tr>
<tr>
<td>Reference</td>
<td>Year</td>
<td>Objective</td>
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<tr>
<td>Aich et al. [9]</td>
<td>2018</td>
<td>Quantify gait parameters using wearable accelerometers; compare five estimated gait parameters with a 3D motion capture system automatic discrimination of FoG patients from no FoG patients using machine learning.</td>
</tr>
<tr>
<td>Diaz et al. [41]</td>
<td>2018</td>
<td>Propose methods to estimate step length and step width using wearable sensors.</td>
</tr>
<tr>
<td>Stack et al. [142]</td>
<td>2018</td>
<td>Detect instability using wearable sensors.</td>
</tr>
<tr>
<td>Zhang et al. [164]</td>
<td>2018</td>
<td>Propose a new gait symmetry index to quantify gait symmetry using one accelerometer.</td>
</tr>
<tr>
<td>Chomiak et al. [29]</td>
<td>2019</td>
<td>Assess the accuracy and reliability of a wearable sensor system for bio-feedback training.</td>
</tr>
<tr>
<td>Grinberg et al. [62]</td>
<td>2019</td>
<td>Investigate different types of 3-meter tandem walking tests in fully ambulatory PwMS.</td>
</tr>
<tr>
<td>Hsied et al. [71]</td>
<td>2019</td>
<td>Determine if a smartphone can measure static postural stability and distinguish elderly with fall risk.</td>
</tr>
<tr>
<td>Mikos et al. [109]</td>
<td>2019</td>
<td>Demonstrate the integration of an FoG detection system into a single sensor node.</td>
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</table>
Table 2.2: (Continued).

<table>
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<tr>
<th>Reference</th>
<th>Year</th>
<th>Objective</th>
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<tbody>
<tr>
<td>Ngueleu et al. [114]</td>
<td>2019</td>
<td>Equip an insole with pressure sensors to detect steps.</td>
</tr>
<tr>
<td>Phan et al. [124]</td>
<td>2019</td>
<td>Investigate wearable sensor technology to identify the kinematic features associated with gait abnormalities seen in cerebellar ataxia.</td>
</tr>
<tr>
<td>Reeves et al. [128]</td>
<td>2019</td>
<td>Determine the between-day reliability of peroneus longus EMG in healthy subjects while walking.</td>
</tr>
<tr>
<td>Rivolta et al. [129]</td>
<td>2019</td>
<td>Investigate the use of wearable accelerometer to evaluate the fall risk determined by the Tinetti clinical scale.</td>
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<tr>
<td>Tang et al. [147]</td>
<td>2019</td>
<td>Propose an objective approach to access functional balance using an insole wearable sensor and an accelerometer.</td>
</tr>
<tr>
<td>Weiss et al. [154]</td>
<td>2019</td>
<td>Evaluate strategies employed by PD patients when transitioning from turning to sitting.</td>
</tr>
<tr>
<td>Zhao et al. [165]</td>
<td>2019</td>
<td>Present an adaptive method for gait detection.</td>
</tr>
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</table>
Table 2.3: Main characteristics of wearable sensors in gait, balance, and RoM research included in the review.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Analysis</th>
<th>Parameters</th>
<th>Population</th>
<th>Sensor(s) Used</th>
<th>Sensor(s) Location</th>
<th>Obtrusiveness Level</th>
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</thead>
<tbody>
<tr>
<td>Van den Noort et al. [151]</td>
<td>ROM</td>
<td>Knee Angle, Ankle Angle</td>
<td>1 healthy</td>
<td>IMU</td>
<td>Thigh</td>
<td>Medium</td>
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<tr>
<td>Franco et al. [51]</td>
<td>Balance, ROM</td>
<td>Trunk angles, Sway ranges</td>
<td>20 healthy</td>
<td>Smart</td>
<td>Lumbar</td>
<td>Low</td>
</tr>
<tr>
<td>Martori et al. [105]</td>
<td>Gait, ROM</td>
<td>Stride length, Cadence, Knee flexion</td>
<td>10 healthy</td>
<td>IMU</td>
<td>Sternum, Waist, Thighs, Shanks</td>
<td>High</td>
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<tr>
<td>Crea et al. [33]</td>
<td>Gait</td>
<td>Swing time, Stance time, Cadence</td>
<td>10 healthy</td>
<td>Pressure</td>
<td>Insole</td>
<td>Low</td>
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</table>
Table 2.3: (Continued).

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<tr>
<td>Hsu et al. [72]</td>
<td>Gait, Balance</td>
<td>Stride time, Stride Velocity, Stance time, Swing time, Cadence</td>
<td>21 AD, 50 healthy IMU</td>
<td>Feet, Waist</td>
<td>Medium</td>
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<td>Patterson et al.</td>
<td>Balance</td>
<td>Postural measure</td>
<td>21 healthy</td>
<td>Smart</td>
<td>Hold on chest</td>
<td>Low</td>
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<td>Reference</td>
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<td>Parameters</td>
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<td>Tzallas et al.</td>
<td>Gait</td>
<td>Not specified</td>
<td>20 PD short-term, 24 PD</td>
<td>IMU</td>
<td>Ankles, Wrists,</td>
<td>High</td>
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<tr>
<td>[150]</td>
<td></td>
<td></td>
<td>long-term</td>
<td></td>
<td>Waist</td>
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<tr>
<td>Wentick et al.</td>
<td>Gait</td>
<td>Gait initiation</td>
<td>3 transfemoral amputees, 3</td>
<td>IMU, EMG</td>
<td>Upper leg</td>
<td>High</td>
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<tr>
<td>[155]</td>
<td></td>
<td></td>
<td>through knee amputees</td>
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<td>Alberts et al.</td>
<td>Balance</td>
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<td>49 healthy one study, 32</td>
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<td>[11, 10]</td>
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Table 2.3: (Continued).

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<tr>
<td>Bauer et al. [16]</td>
<td>ROM</td>
<td>Flexion, Extension, Lateral</td>
<td>22 asymtomatic validity, 24 asymtomatic reliability</td>
<td>IMU</td>
<td>Right thigh, Sacrum, L1 back level, T1 back level</td>
<td>Medium</td>
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<tr>
<td>Ellis &amp; Zhu et al. [166, 46]</td>
<td>Gait</td>
<td>Step time, Step length, Variability</td>
<td>12 healthy elderly, 12 PD</td>
<td>Smart Abdomen</td>
<td>Low</td>
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<tr>
<td>Godfrey et al. [57]</td>
<td>Gait</td>
<td>Step length, Step velocity, Asymmetry</td>
<td>40 healthy young, 40 healthy old</td>
<td>IMU Lumbar</td>
<td>Low</td>
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<tr>
<td>Jaysrichai et al. [76]</td>
<td>ROM</td>
<td>Knee angle</td>
<td>10 healthy</td>
<td>IMU Shanks, Thighs</td>
<td>Medium</td>
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</table>


Table 2.3: (Continued).

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<tr>
<td>Kanzler et al. [77]</td>
<td>Gait</td>
<td>Heel clearance, Toe clearance, Foot angle</td>
<td>20 healthy IMU</td>
<td>Ankle</td>
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<tr>
<td>Lee &amp; Kumar et al. [92, 84]</td>
<td>ROM Joint angles</td>
<td>19 healthy, 20 disable IMU, Smart Thighs, Shanks, Ankles</td>
<td>High</td>
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<td>Lin et al. [97]</td>
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<td>Step count</td>
<td>10 healthy Pressure Insole</td>
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<tr>
<td>Postolache et al. [127]</td>
<td>Gait Step length, Stride length, Cadence, Gait Speed</td>
<td>6 healthy IMU, Pressure Shanks, Insole</td>
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<tr>
<td>Sijobert et al. [139]</td>
<td>Gait Stride length</td>
<td>10 healthy, 12 IMU</td>
<td>Shanks</td>
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<td>Sensor(s) Location</td>
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<tr>
<td>Bertolotti et al. [19]</td>
<td>Balance, ROM</td>
<td>Trunk inclination, Sway path, Sway area, Sway mean velocity</td>
<td>10 healthy</td>
<td>IMU</td>
<td>Lumbar</td>
<td>Low</td>
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<tr>
<td>Del Din et al. [36]</td>
<td>Gait</td>
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<td>IMU</td>
<td>Lumbar</td>
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<td>Horak et al. [68]</td>
<td>Gait, Balance</td>
<td>Postural measures, Trunk acceleration,</td>
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<td>IMU</td>
<td>Lumbar, Shanks, Arms</td>
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<td>Gait speed, Cadence</td>
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<tr>
<td>Lee et al. [91]</td>
<td>Gait, Balance</td>
<td>Jerk, Sway range, Sit-to-stand time,</td>
<td>65 elderly</td>
<td>IMU</td>
<td>Lumbar</td>
<td>Low</td>
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<td>Mean &amp; STD, Step length</td>
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<tr>
<td>LeMoyne et al. [93]</td>
<td>Gait</td>
<td>Stride time, Gyroscope statistics</td>
<td>1 healthy, 1 FA</td>
<td>IMU</td>
<td>Ankles</td>
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<tr>
<td>Li et al. [96]</td>
<td>Gait, Balance</td>
<td>Trunk angle, Muscle strength</td>
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<td>EMG, Smart</td>
<td>Lumbar, Thighs</td>
<td>Medium</td>
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<td>Parameters</td>
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<tr>
<td>Storm et al. [144]</td>
<td>Gait</td>
<td>Stride time, Step time, Stance times</td>
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<td>IMU</td>
<td>Lumbar, Ankles</td>
<td>Low</td>
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<tr>
<td>Wang et al. [153]</td>
<td>Gait</td>
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<td>10 healthy, 1 Hemiphereis</td>
<td>EMG</td>
<td>Legs muscle</td>
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<td>Andó et al. [13]</td>
<td>Balance</td>
<td>Sway range, Sway mean velocity, Sway mean frequency</td>
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<td>IMU</td>
<td>Waist, Sternum</td>
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<td>Iijima et al. [75]</td>
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<td>Gait cycle, Cadence, Acceleration magnitude</td>
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<td>IMU</td>
<td>Waist</td>
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<tr>
<td>Lebel et al. [90]</td>
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<td>Multiple ROM angles</td>
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<td>IMU</td>
<td>Left feet, Pelvis, Back, Head, Left, Calf, Left Thigh</td>
<td>High</td>
</tr>
<tr>
<td>Reference</td>
<td>Analysis</td>
<td>Parameters</td>
<td>Population</td>
<td>Sensor(s) Used</td>
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<tr>
<td>Robert-Lachaine et al. [130]</td>
<td>ROM</td>
<td>Multiple ROM angles</td>
<td>12 healthy IMU Feet, Shanks, Arms, Thighs, Pelvis, Sternum, Head</td>
<td>IMU</td>
<td>Feet, Shanks, High</td>
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<tr>
<td>Schlachetzki et al. [132]</td>
<td>Gait</td>
<td>Stride length, Stride time, Velocity, Gait phases times, Foot clearance, Heel-strike, Toe-off angles</td>
<td>63 PD IMU Ankle</td>
<td>IMU</td>
<td>Ankle</td>
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<tr>
<td>Shazad et al. [136]</td>
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<td>Step count, Step frequency, Avg. step length, Walking speed</td>
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<td>Gait</td>
<td>Step time, Stride time, Step length, Stride length, Walking speed</td>
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<td>Diaz et al. [41]</td>
<td>Gait</td>
<td>Step length, Step width</td>
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<td>Lumbar, Thighs, Shanks</td>
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<tr>
<td>Stack et al. [142]</td>
<td>Gait, Balance</td>
<td>TUG Times, Turns’ Step Count</td>
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<td>IMU</td>
<td>Wrist, Ankle, Waist</td>
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<td>Zhang et al. [164]</td>
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<td>Feet, Lower Back</td>
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<td>Chomiak et al. [29]</td>
<td>Gait</td>
<td>Walking speed, Cadence, Step length</td>
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<td>Grinberg et al. [62]</td>
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<td>Mazzeta et al. [106]</td>
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<td>Step time, Ratio: Max value/sEMG</td>
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<td>IMU-calf, EMG-lower leg</td>
<td>High</td>
</tr>
<tr>
<td>Mikos et al. [109]</td>
<td>Gait</td>
<td>Frequency, RMS &amp; STD, Range, Stride length, Stride time</td>
<td>63 PD</td>
<td>IMU</td>
<td>Ankles</td>
<td>Low</td>
</tr>
</tbody>
</table>
Table 2.3: (Continued).

<table>
<thead>
<tr>
<th>Reference</th>
<th>Analysis</th>
<th>Parameters</th>
<th>Population</th>
<th>Sensor(s) Used</th>
<th>Sensor(s) Location</th>
<th>Obtrusiveness Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ngueleu et al. [114]</td>
<td>Gait</td>
<td>Step Count</td>
<td>20 healthy</td>
<td>Pressure</td>
<td>Insole</td>
<td>Low</td>
</tr>
<tr>
<td>Phan et al. [124]</td>
<td>Gait</td>
<td>PCA generated features</td>
<td>29 cerebellar ataxia, 22 healthy</td>
<td>IMU</td>
<td>Ankles</td>
<td>Low</td>
</tr>
<tr>
<td>Reeves et al. [128]</td>
<td>Gait</td>
<td>Peroneus longus</td>
<td>10 healthy</td>
<td>EMG</td>
<td>Right leg, Medium (SENIAM guideline)</td>
<td></td>
</tr>
<tr>
<td>Rivolta et al. [129]</td>
<td>Gait, Balance, ROM</td>
<td>Accelerometer features, Tilt angle</td>
<td>79 hospitalized</td>
<td>IMU</td>
<td>Chest</td>
<td>Low</td>
</tr>
<tr>
<td>Reference</td>
<td>Analysis</td>
<td>Parameters</td>
<td>Population</td>
<td>Sensor(s) Used</td>
<td>Sensor(s) Location</td>
<td>Obtrusiveness Level</td>
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</tr>
<tr>
<td>Tang et al. [147]</td>
<td>Gait, Balance</td>
<td>RMS &amp; STD, Entropy, Mean absolute deviation, Lempel-Ziv, Dominant frequency</td>
<td>33 elderly</td>
<td>IMU, Pressure</td>
<td>Waist pouch, Insole</td>
<td>Low</td>
</tr>
<tr>
<td>Weiss et al. [154]</td>
<td>Balance</td>
<td>TUG times</td>
<td>96 PD</td>
<td>IMU</td>
<td>Lumbar</td>
<td>Low</td>
</tr>
<tr>
<td>Zhao et al. [165]</td>
<td>Gait</td>
<td>Gait cycle</td>
<td>9 healthy</td>
<td>IMU</td>
<td>Feet</td>
<td>Low</td>
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</table>
2.2.1 Common Wearable Sensors Used in Movement Assessment

Wearable sensors are devices that are mounted to a person’s body to gather information, such as movement or heart rate. Wearable sensors typically are not expensive and are small in size. Wearable sensors are playing an increasing role in balance and gait assessment in rehabilitation research. Three important advantages of wearable sensors for assessment of gait and balance disorders are that they can [67]:

- obtain objective measures that characterize how and why functional performance of gait and balance are impaired,
- increase the sensitivity of gait and balance measures, and
- increase the opportunity for immediate biofeedback to patients.

In the next following sections the common wearable sensors used in gait, balance, and RoM analysis are described.

2.2.1.1 Inertial Measurement Units and Magnetometers

Inertial measurement units (IMUs) are devices that typically contain an accelerometer, a gyroscope, and sometimes, a non-inertial sensor called a magnetometer [74]. There are numerous types of IMUs developed by different companies, although the size and weight of these devices are similar. The primary differences between sensors developed by different companies are in software, the algorithms used to analyze the data, and the housing in which they are mounted. The housing varies depending on the battery and on-board storage. The information collected from these devices depends on the subject’s movements performed while wearing the devices.

Accelerometers are the most common sensor used in gait, balance, and RoM research using IMU devices. Accelerometers are embedded within wearable sensors and the data is often gathered in three dimensions, i.e., acceleration forces in the $X$, $Y$, and $Z$ axes. These forces may be caused by the constant force of gravity pulling at the feet or caused by moving
or vibrating the accelerometer. Some researchers prefer a single signal of acceleration in order to be orientation invariant, thus, avoiding misalignment issues [78]. To achieve this, the magnitude of the acceleration using three-dimensional data is calculated using Equation (2.1), where $a_x$, $a_y$, and $a_z$ are the accelerations in the $X$, $Y$, and $Z$ axes, respectively.

$$a_m = \sqrt{a_x^2 + a_y^2 + a_z^2}$$  

(2.1)

A gyroscope is a sensor that uses the Earth’s gravity to help determine orientation and angular velocity. Usually, its design consists of a freely-rotating disk mounted into a spinning axis in the center of a larger and more stable wheel. When the axis turns, the disk remains stationary to indicate central gravitational pull. The main difference between the accelerometer and gyroscope is that one can sense rotation and the other cannot [58]. In a stationary scenario, the accelerometer can determine orientation with relation to Earth’s surface, but when acceleration is applied to the device, the accelerometer is unable to differentiate between that movement and the acceleration provided through gravitational pull [58].

A magnetometer is a non-inertial sensor that measures magnetic fields. A simple type of magnetometer is a compass, which provides a simple orientation in relation to the Earth’s magnetic field. Magnetometers, in ubiquitous computing applications, are often used to improve measurements regarding orientation, especially heading. However, as challenge in the application of magnetometer readings is that magnetic disturbances limits the accuracy of their measurements. Fortunately, there are ways to compensate for these errors, which will be discussed in Section 2.3.11.

2.2.1.2 Smart Devices

Smart devices, such as smartphones and smart watches, are very popular because of their low cost, high availability, and capability to behave as an IMU device. Smart devices contain
similar componentry as IMUs, including accelerometers, gyroscopes, and magnetometers. Researchers investigate the potential use of smart devices to assess gait, balance, and RoM to reduce the level of obtrusiveness that using multiple devices can introduce and to increase portability. For example, there are studies that implement smart devices to measure trunk movements and postural stability to assess balance [51, 120, 11, 10, 96, 71]. Other studies quantify gait parameters using symmetry and variability [166, 46, 29, 30].

2.2.1.3 Electromyography Sensors

Electromyography (EMG) sensors use electrodes to record electrical activity from subject’s muscle tissue. There are two types of EMG sensors: surface electrodes and needle electrodes. Needle electrode exams are more specific and accurate. EMG sensors can detect whenever a muscle is at rest or active; a negative electrical potential difference is maintained across the muscle when the muscle is resting, while a positive potential travels along the length of the fiber when the nerve activates the muscle fiber [15].

EMG is an essential tool in diagnostic evaluation of patients with peripheral neurologic disorders, such as peripheral neuropathy, Guillain Barre, or ALS [34]. EMG has contributed in multiple clinical areas to enhance the management of patients with neuromuscular disorders, including neurology, neurosurgery, and orthopedics [148], and is often used in combination with nerve conduction velocity tests. EMG and nerve conduction velocity provide different information about the peripheral nervous system, but when analyzed together, aid in accurate diagnosis [34]. EMG and surface EMG (SEMG) have been used to identify certain gait characteristics, distinguish compensatory balance responses, and develop and improve methods used to assess balance. Continuous EMG analysis in patients with neurological disorders provide relevant diagnostic contributions in terms of nosological classification, localization of focal impairments, detection of pathophysiological mechanisms, and functional assessment to supplement the clinical evaluation of neuromuscular disorders [155, 96, 106, 128]. However, EMG has limitations and considerations [34, 63, 80]:
• technical limitations may be present in cases of obesity or advanced age,

• EMG cannot be used for all muscles for all activities,

• EMG does not give RoM information,

• electrode placement is vital,

• traditional EMG cannot detect passive movements, and

• for SEMG, skin must be cleaned and static charges on the skin can alter the signals.

2.2.1.4 Insole Pressure and Force Sensors

Besides measuring body movement with IMUs and smart devices and measuring muscle electrical activity with EMG, there are sensors that can measure ground reaction forces applied by the subject. The pressure sensor is typically located in the insole of the subject’s shoes, and it can measure the plantar foot surface in three dimensions. The most common insole sensors are capacitive, resistive piezoelectric, and piezoresistive sensors; which is selected depends on the range of pressure it can stand and it’s sensitivity [112]. Insole pressure sensors are known for being unobtrusive and for their potential in monitoring daily activities since people wear shoes for multiple hours a day. They are typically used in gait analysis to count steps and extract time and distance-based parameters. In balance analysis, they are typically used to measure center of pressure to evaluate postural stability [33, 97, 127, 114, 99].

2.3 Design Issues in Gait, Balance and RoM Wearable Systems

The following outlines the most important challenges to consider in the design and implementation of systems that use wearable sensor technology to assess gait, balance, and RoM.
2.3.1 Obtrusiveness

The number of wearable sensors used in a system can be associated with the level of obtrusiveness of the system. It is known that having more sources of data in a system will provide more information. However, there is the disadvantage of decreased subject comfort as the number of sensors increases. Additionally, not all sensors are completely wireless since there are sensors that require the use of wires or electrodes, such as the EMG devices, to extract information, also affecting the level of obtrusiveness. Researchers often encounter the problem of accuracy versus subject comfort — that is, having to decide to either build a system with high accuracy using multiple sensors, or build a system with lower accuracy and less data using fewer sensors. Fewer sensors allow the subject to feel more comfortable, and avoids interfering with trial performance or daily activities. Decreasing the number of sensors can also be beneficial in terms of complexity, cost, and the amount of data to process. From the studies included in this review, 33 had 2 or fewer sensors, thus having a low level of obtrusiveness. On the other hand, 10 were considered to have a medium level obtrusiveness with 3 or 4 sensors, and 13 high level obtrusiveness with 5 or more sensors, or had multiple straps or cables to hold the sensor in place.

2.3.2 Sensor Location

Wearable sensors eliminate the location limitation set by external sensors, but they yield another complication. Selecting locations on the subject’s body to mount the sensors is a difficult decision, especially when the number of sensors available is limited. It is extremely important to decide optimal locations since the performance of the system and the data obtained depends on it. Studies using wearable sensors vary greatly in terms of body locations selected to mount sensors, however, the most common areas are the sternum, waist, lumbar, lower back, and different upper or lower extremity locations, such as the wrists, thighs, ankle, heels, and feet. The selection of sensor locations depends on the gait, balance, and RoM parameters to be measured. For static balance assessment, the most common locations
are lumbar, waist, and/or holding the device in the chest/sternum due to the capability of measuring trunk sway at these locations (Table 2.3). The most reliable step count comes from insole pressure sensor since it can detect the pressure applied to the sensor once a subject is performing a step [33, 97, 127, 114]. Studies that use IMUs for gait analysis tend to mount the devices on locations below the knee joint, such as feet, ankles and shanks, due to the high movements involved in those areas when a person is walking (Table 2.3).

2.3.3 Sensor-to-Segment Alignment

After sensor locations are selected, another problem is sensor-to-segment alignment, or the orientation of each sensor relative to the assigned segment previously selected. One study indicated that the position of the sensor relative to the segment is usually far less important for obtaining valid segment orientations compared to the sensor-to-segment alignment [108, 169]. Calibration procedures to address this problem have been proposed, such as static pose calibration, requiring the user to take on specific poses, functional calibration, requiring the user to perform movements around defined axes, and technical calibration, requiring manual alignment with respect to the bone structure [169, 22, 118, 35]. These procedures still have potentially large human-induced errors and researchers have started to study ways to integrate machine learning and deep learning techniques to help improve inaccuracies [41, 93, 109, 116, 115].

2.3.4 Soft Tissue Artifact

A challenge in human motion analysis arises from soft tissue artifact (STA), resulting from the unequal movement of soft tissue layers (muscle, tendon, and dermis) between the bone and the skin surface [49]. Typically, relative translation and relative rotation are assumed to show the majority of STA, in which yields to be the components targeted for mitigation [52]. Another way to mitigate STA is by processing the translational acceleration and rotational velocity measured by an IMU [117]. Only a few studies included in this review handled soft
tissue artifact in different ways. A common way is to place the devices over the bones and not over the muscles to reduce soft tissue artifact [130]. Additionally, using bundles and straps and having care in positioning the bundles can minimize soft tissue artifact [90].

Additionally, STA also occurs in optoelectronic systems when placing markers to the subject’s segments. This needs to be taken into consideration since optoelectronic systems are often used to validate wearable sensor measurements [90, 130, 41, 151, 9]. Some ways to minimize this issue is by having the marker within the field of view of at least two cameras, markers attached to the same segment should be distributed to minimize position error propagation to bone orientation, and the movement between underlying bones and the markers should be minimal [25, 27, 24, 23, 89].

2.3.5 Processing

Once the data is collected, the researcher has to decide how to process the data and this largely depends on the system used. If a wearable sensor system does not have the capability of running the algorithms locally, servers are preferred since they have a large amount of storage space, processing power, and energy capabilities that allow complex data and algorithms. This approach is really common when machine learning techniques are used because these techniques often require high computational and processing power in order to train the models [41, 9, 109, 116, 115]. Systems connected to smartphones can run the algorithms locally if the complexity of the data and algorithms allow it, which depends on the device’s limitations of storage, battery, and processing power. Twelve studies included in this review followed the smart device-based approach (Table 2.3). Depending on the processing approach, it may affect the waiting time of the subjects between each trial because the computational cost and processing power influence how fast the users can obtain results.
2.3.6 Energy Consumption

Communication is usually the most energy consuming operation, therefore researchers should minimize the amount of data transmitted. Short range wireless networks, such as Bluetooth or Wi-Fi, should be preferred over long range networks since they use less power. There are methods to reduce the energy consumption, such as data aggregation and compression, but they may jeopardize the system’s performance.

The number of sensors used also have an impact on the system’s energy consumption. It is obvious that the more sensors used, the more energy the system consumes. This is another reason why studies tend to use fewer sensors. Another direct and simple solution to this issue is when the sensors are not being used, they can be turned off.

2.3.7 Mobility

A common reason to use wearable sensors is to provide a high level of mobility and portability. Systems that use servers to analyze the data often require access to the internet. This makes the system location dependent since they would not work in locations where internet is not available such as outdoors. This leads to a system that is not completely mobile. Studies that use smart devices usually do not have this issue because of the high capability of connecting to the internet to run their own methods to evaluate the subject’s gait, balance, and RoM regardless of the location being assessed (Table 2.3).

2.3.8 Cost

As previously mentioned, wearable sensors are cheaper than external sensors. However, this does not mean that cost is not an issue with wearable sensors. Cost can increase for multiple reasons, such as the number of sensors used, type, brand, and computer equipment and software needed to process the data. Researchers and clinicians with low resources may not be able to afford costly wearable sensor systems. That is why some researchers tend to evaluate the subjects using smart devices, such as smartphones, since nowadays millions of
people already own one (Table 2.3). Others prefer to build their own device using their own specifications to reduce the cost [19].

2.3.9 Noise

Noise is irregular fluctuations within the signal monitored. If noise is not filtered out, the results attained may be inaccurate. Wearable sensor noise is generated by the electrical and mechanical components. Common considerations to reduce noise in a system using accelerometers are cables and shield [19]. Most wearable sensors are wireless, eliminating cable noise. Modern wearable devices shield the sensors embedded in the device to protect them from noises produced by external signals [94]. Sometimes these techniques are not sufficient and the measured signal contains measurement errors. In this case, noise is known to be the high-frequency portion of the measurement errors and thresholds and filtering techniques are used to clean the signals extracted from the sensors [16, 153, 116, 115, 139].

2.3.10 Thresholds

A threshold is a limit used to trigger an action when that limit is surpassed. Various systems use thresholds to make decisions and conclusions about the data behavior. The most common solution is to set thresholds that generalizes the data as much as possible. Additionally, there are studies that investigated the use of thresholds with filtering techniques to extract useful gait, balance, and RoM parameters from wearable sensors [11, 10, 153, 116, 115, 139]. Another way to avoid setting thresholds is by using machine learning techniques. By using these techniques, the algorithms are trained to learn the most optimal threshold for a specific problem or measurement [169, 41, 93, 136, 9, 30, 109].

Systems should provide the option to adjust thresholds since they should be optimized to the movements to give the most reliable and accurate measurements. Otherwise, the data yields misleading results, which may affect decisions made by researchers of professionals making rehabilitation decisions.
2.3.11 Magnetic Disturbances

A challenge in the application of IMUs is that the magnetic field is known to be inhomogeneous in indoor environments and near ferromagnetic materials. These disturbances limit the accuracy of measured parameters in two ways: sensor orientation estimates are deteriorated, and magnetic disturbances may limit the accuracy of the sensor-to-segment calibration [86]. To avoid magnetic disturbances, some researchers use non-magnetic equipment to perform the assessment, such as a couch with wooden frames [151]. There are others that use Kalman filters and sensor fusion techniques to minimize the disturbance applied to the signals being evaluated [130, 51, 131, 86].

2.3.12 Sensor Fusion

Wearable sensor systems relying on single or multiple sensors present limitations such as sensor deprivation, limited spatial coverage, and imprecision [47, 113]. Sensor fusion is an effective solution to address these problems. Sensor fusion can be competitive, complementary, and cooperative [161]. Competitive fusion uses multiple equivalent sources of information to obtain redundancy and self-calibration. In complementary fusion, each sensor captures different aspects of what is being monitored to improve system accuracy and reliability. Cooperative fusion is when multiple sensor signals are needed to obtain information that was not obtained by any of the signals independently [61]. When it comes to data processing level, sensor fusion is divided into three categories:

- Data-level Fusion: implements de-noising, feature extraction, data classification, and data compression,

- Feature-level Fusion: creates a new high-dimension feature set that represents the input for classification or pattern recognition, and

- Decision-level Fusion: utilizes the abstracted information from either data-level or feature-level fusion to make a decision [61].
The fusion level used in a wearable sensor system will affect other issues such as processing, information loss, and performance. There are instances when sensor fusion is necessary to provide more accurate measurements. For example, when researchers want to know the orientation of an IMU, it may not be sufficient to just use an accelerometer because this may yield inaccurate results. It is not possible to extract heading of the sensor with just an accelerometer, but fusing an accelerometer and magnetometer provides this additional information critical to examine postural control and RoM [86]. Fusing the accelerometer, gyroscope, and magnetometer data helps to improve the accuracy of these measurements.

2.4 A Taxonomy for Gait, Balance, and RoM Analysis

A taxonomy for wearable sensor technology that allows comparison of different systems that share similar characteristics and capabilities is presented in Figure 2.2 [42]. We categorized these systems into two levels. The first level specifies the analysis to be performed, which can be either gait analysis, balance assessment, or Range of Motion (RoM) analysis. The second level specifies the categories of parameters extracted from the analysis, which can include rhythm and phase, pace, variability, postural control, or asymmetry. Rhythm and phase parameters are variables that reflect gait rhythm, timing, and duration; pace parameters give information about speed and/or length measurements; postural control is an integrative process used to maintain body’s position relative to gravity and of its segments relative to each other; asymmetry parameters are those that look for differences between limbs; and variability is the fluctuation of parameters, which can offer a complementary way of quantifying and indicating mobility deficits [59].
2.4.1 Gait Analysis

One of the main goals of physical therapy and rehabilitation is that ambulatory patients achieve independent walking. Physical therapists use gait analysis to determine what causes patients to walk the way that they do. The goal of clinical gait analysis is to assist in plan of care decision-making for patients to help ameliorate the gait deviations so that the patient may walk more efficiently and independently [20]. Additionally, gait analysis studies the natural history of change in walking over time in neurodegenerative diseases or changes in gait after implementing interventions [67, 101].

Walking is the result of a cyclic series of movements that can be characterized by a description of its fundamental unit, the gait cycle. A gait cycle is the time period of events during locomotion in which one heel makes contact with the ground and that same foot makes contact with the ground again; a single gait cycle is also known as stride. A step is the sequence of events that occurs within successive heel contacts of opposite feet. Step and/or stride detection is the first task that researchers try to accomplish when using wearable sensors to conduct gait analysis. The most common method to perform step and/or
Stride detection using IMU and smart devices is by using peak detection algorithms on accelerometer data [72, 36, 166, 46]. Step and/or stride detection is easier when using insole pressure sensors since the pressure applied to the sensor when the foot is in contact with the ground is higher than when it is not in contact with the ground [155, 115, 153, 96, 106, 128]. However, people that are affected by neurological disorders tend to shuffle and/or drag their feet when walking, performing short and dragged steps, which makes it harder to detect heel strikes or foot contact [125].

2.4.1.1 Gait Analysis: Rhythm and Phases

The most common gait parameters associated with rhythm and phases of gait are gait cycles phases, stance time, swing time, step time, stride time, cadence, and walking ratio [15, 59].

In the gait cycle, there are two main phases called stance phase and swing phase. In the stance phase, the foot is in contact with the floor, while in the swing phase, the foot is moving through the air without making contact with the floor. However, researchers continue to expand the gait phases involved in a gait cycle to have a deeper and more detailed understanding of the gait cycle. Taborri et al. standardized the name of the different gait phases, going from the two main phases, stance phase and swing phase, to a granularity of phases: initial contact, loading response, mid stance, terminal stance, pre swing, initial swing, mid swing, and terminal swing [146].

Researchers measure the time it takes subjects to complete each phase of gait. Swing time is the time that passes during swing phase, starting as soon as the foot leaves the floor until it makes contact with the floor again. Stance time is the time that passes during the stance phase, starting once the foot makes contact with the floor until it moves off the floor again. Researchers have found that a stance phase is longer when the subject has a balance problem [59]. Stride time is the duration of a stride, and the same procedure used to measure swing time and stance time can be used to calculate stride time. It can also be measured by
adding up the swing time plus the stance time. Step time is the duration of a step. When
data is recorded from wearable sensors, the data includes a timestamp. A timestamp is the
time registered to a file or log that records when an event or data is added, removed, or
modified. It is possible to calculate time-based parameters by subtracting the timestamp of
when the previous event occurred minus the timestamp of when the current event occurred
[33, 72, 36, 144, 166, 46, 93, 9, 109].

Cadence is the rate at which a subject walks, expressed in steps per minute. Researchers
have found that cadence is usually between 98–138 steps per minute for healthy women and
91–135 steps per minute for healthy men, between the ages of 18–49 [156]. Researchers
often approximate cadence by using a mean step time. As an example, if a subject’s mean
step time is around 0.5s, the subject will execute approximately 120 steps in a minute.
Using mean step time may not be ideal when the subject’s walking pattern is asymmetrical.
Cadence has been used to give quantitative data that serve as early indicators of neurological
disorders, assess the daily living walking activities, and provide immediate bio-feedbacks
[105, 33, 72, 127, 75, 29].

Walking ratio represents the relationship between frequency and amplitude of movements
of the legs. It can be calculated by dividing the mean step length by the cadence. Researchers
have found that the mean walking ratio is 0.58 and it decreases when the person walks with
fast, shorter steps, which might present with individuals diagnosed with Parkinson’s or
Alzheimer’s disease [59].

2.4.1.2 Gait Analysis: Pace

The parameters that represents pace include step length, stride length, and walking speed
(or gait velocity). Step length is the distance between one foot’s heel-strike to the opposite
foot’s heel-strike when walking. Stride length is the distance travelled by a person when they
perform a stride; i.e., the distance from one foot’s heel-strike to the next heel-strike of the
same foot. Step and stride length can be calculated once the steps are detected. Knowing the
step and stride lengths helps to determine how symmetric the subject is walking. Researchers have discovered that step length is affected linearly by walking frequency and acceleration variance [137]. Walking frequency (WF) can be calculated using Equation (2.2), where \(WF_k\) is the walking frequency for step \(k\) and \(t_k - t_{k-1}\) is the step time for step \(k\). Acceleration variance (AV) can be calculated using Equation (2.3), where \(AV_k\) is the acceleration variance for step \(k\), \(n_k\) is the number of samples during the sequence of step \(k\), \(a_{k,i}\) is the acceleration at time \(i\)-th on step \(k\), and \(\bar{a}_k\) is the acceleration mean during the same sequence of step \(k\).

\[
WF_k = \frac{1}{t_k - t_{k-1}} \tag{2.2}
\]

\[
AV_k = \frac{1}{n_k - 1} \sum_{i=1}^{n_k} (a_{k,i} - \bar{a}_k)^2 \tag{2.3}
\]

After walking frequency and acceleration variance are calculated, then step length (SL) can be determined using a linear approximation (Equation (2.4)), where \(\alpha\), \(\beta\) and \(\gamma\) are the step length estimation constant parameters for the linear equation [137].

\[
SL_k = \alpha \cdot WF_k + \beta \cdot AV_k + \gamma \tag{2.4}
\]

Other researchers have calculated step length using the change of height of the center of mass, \(h\), (vertical position) and the length of a pendulum, \(l\), (sensor height from the ground), as shown in Equation (2.5) [168, 36]. Once step lengths are calculated, stride length can be determined by adding the left step length to the right step length.

\[
SL = 2 \cdot \sqrt{2lh - h^2} \tag{2.5}
\]

Step length and stride length has been used in the literature to compare the variability pre- and post-training as well as the variability between healthy subjects and subjects with a particular neurological disorder [105, 166, 46, 57, 127, 139, 91, 136, 41, 29, 109].
Gait velocity, also known as walking speed, is the distance travelled in a given period of time and is thought to be indicative of a person’s functional capacity [53, 107]. Gait speed represents the overall performance of the walking pattern. According to Baker, it can be calculated using Equation (2.6), where gait velocity (GV) is expressed in meters per second, cadence is in steps per minute, and stride length (SL) is in meters [15]. Researchers have found that while cadence increases linearly, step length increases logarithmically, and it tends to stabilize at high speeds but changes at low speeds [59]. Gait velocity is correlated with functional ability and balance confidence and can be used to determine outcomes such as functional status, discharge location, and the need of rehabilitation [53].

\[
GV = \frac{\text{Cadence} \times SL}{120}
\] (2.6)

Gait velocity estimation algorithms can be divided into three categories: abstraction model, human gait model, and direct integration [162]. Abstraction model takes advantage of machine learning techniques to approximate the speed and decide to ignore the details of the human gait biomechanics; human gait models estimate the gait velocity by using the stride length of the subject; and lastly, direct integration method is when the acceleration of the sensor is integrated in the global coordinate system from the starting point to obtain instantaneous sensor velocity and the associated stride length. Direct integration is the most common approach used in gait and balance studies [162]. Direct integration seems like a straight-forward approach, but the accuracy of the integration can be inaccurate since the gravitational force is difficult to separate from the inertial force.

Walking speed is considered the “sixth vital sign” for its capabilities, reliability, and sensitivity that it can measure to assess and monitor overall health [53, 107]. These led researchers to use walking speed to provide bio-feedback training, assess fall-risk and server as an indicator of a neurological disorder [72, 127, 68, 136, 9, 29].
2.4.1.3 Gait Analysis: Variability

Variability can be expressed in terms of measures of dispersion, such as standard deviation and/or coefficient of variation [65]. Variability can be detected temporally or spatially, similar to asymmetry. Research informs that variability in spatiotemporal parameters predicts mobility deficits and future falls better than other gait parameters [59]. On the other hand, researchers have concerns about the best way to measure variability. This leads to questions about how many parameters to use to measure variability; for example, whether to measure it temporally or spatially, and whether to measure variability for each lower limb separately or combined.

Gouelle et al. proposed a new way to quantify fluctuation magnitude using the Gait Deviation Index as reference and developed a Gait Variability Index (GVI) [134, 60]. The GVI is based on nine weighted (using Principal Component Analysis) gait parameters: step length, stride length, step time, stride time, swing time, stance time, single support time, double support time, and velocity. It uses the difference between the variability of an individual compared with a reference group. The value obtained is transformed into a score with 100 and 10 representing the mean and standard deviation, respectively, of the reference.

Non-linear variability is also gaining acceptance within the gait analysis community, such as Lyapunov exponent (LyE). Huisinga et al. quantified the temporal structure of the trunk acceleration time series from both direction using LyE and approximate entropy [73]. The largest LyE is a measure of the rate at which nearby trajectories in state space diverge; lack of divergence in the acceleration pattern will produce small values for the LyE and vice versa [73]. They demonstrated that in people with multiple sclerosis the acceleration time series increased LyE in both medio-lateral and antero-posterior directions, which indicates excessive divergence and reduced behavioral complexity as compared to healthy subjects [73].

Another way to measure variability using wearable devices is to extract statistical parameters. Two of the most common statistical parameters used to represent variability are
standard deviation and coefficient of variation [36, 166, 46, 60]. These are calculated by using spatiotemporal parameters such as step length, step time, single support time, and others, since they have shown in the literature to being able to assess fall risk. However, these are sometimes not recommended since these measures of dispersion can present bias and alter the results: standard deviation is sensitive to the scale, and coefficient of variation tends to infinity when the mean is close to 0 [60].

2.4.1.4 Gait Analysis: Postural Control

The main parameters in this category are step width and foot angle. Step width measures the separation of the feet while walking. Step width is usually 8-12 centimeters in children and adults [59]. Changes in step width can be seen when people have balance problems and when patients walk faster. People with a balance disorder usually expand their step width; while people that walk faster tend to decrease their step width. The foot angle can be defined as the angle of rotation during stance. Usually, the angle ranges from 0-15 degrees in normal, healthy adults. Excessive foot angle or toe out can be an indication of walking abnormalities and is often seen in children with cerebral palsy or adults with stroke [59]. Unfortunately, these parameters are complex to measure using wearable sensors and accurate methods to extract these parameters using wearable sensors are limited [41].

Another common criterion studied by researchers and related to postural control is the walk deviation. Walk deviation is when a person attempts to walk in a straight line but is unable to achieve it and strays off the line. Perez and Labrador calculated walk deviation from a walking path using the rotation vector sensor of a smartphone [122]. They incorporated used of the Functional Gait Assessment (FGA) walking path level markers (Figure 2.3).
The FGA determines the risk of falling by assessing postural stability during gait. To perform the FGA, they used a 6.096 meter long walkway with a 30.48 centimeters (cm) lateral path. To assess walk deviation, markers are placed on both sides of the walkway, each one corresponding to a specific deviation level. The level range is from 0 to 3, level 0 meaning no or small deviation and level 3 meaning high deviation.

Perez and Labrador detected the deviation $D_i$ for step $i$ by using the step length and the angle of rotation for that specific step (Equation (2.7), Figure 2.4) [95, 122]. The angle of rotation is extracted from the rotation vector samples.

$$D_i = SL \times \sin(\theta_i)$$  \hspace{1cm} (2.7)
Additionally, the cumulative deviation can be calculated (Equation (2.8)) to check the total deviation from the starting to end point [122], where $D_{\text{sum}}^0$ is equal to 0.

$$D_{\text{sum}}^i = D_i + D_{\text{sum}}^{i-1} \quad (2.8)$$

### 2.4.1.5 Gait Analysis: Asymmetry

Gait asymmetry can be expressed in two different ways: *temporal asymmetry* and *spatial asymmetry* [59]. In spatial asymmetry, the step length values are unequal, while in temporal asymmetry there is a difference in time spent in swing and/or stance phase between the two feet. In a temporal symmetric walking pattern, the steps and strides are equal. In the case of a temporal asymmetric walking pattern, step lengths are different between the two legs but stride lengths are equal. Two common ways to represent symmetry are by differences or ratios [57, 36]. In differences, the values are subtracted (i.e., left-right) from each other, in which 0 represents perfect symmetry. Using ratios, the values are divided (e.g., left/right), in which 1 represents perfect symmetry.

Another two approaches have been used to represent symmetry: Dynamic Time Warping (DTW) algorithm and Autocorrelation. DTW is popular because it is extremely efficient in measuring time-series similarities, thus minimizing the effects of shifting and distortion in time, and allowing transformation of time series in order to detect similar shapes with different phases [135]. The algorithm can be applied by comparing two acceleration signals of different steps to see if there are any differences between one step and the other.

Autocorrelation is the correlation between a signal with a delay copy of itself and has been widely used to find repeated patterns in a signal [95, 122]. Accelerometer signals from wearable sensors provide information to be used in the algorithm. Researchers have demonstrated that low values in the coefficient of the first and second dominant period represent a low regularity between steps and cycles and the ratio of both coefficients represents symmetry between left and right steps [110]. Researchers used these techniques to check similarities.
between different steps and to capture a walking pattern problem if an impediment was present [153, 95, 122].

Gait asymmetry has shown to be an important marker of mobility impairment [164]. Recently, a Gait Symmetry Index (GSI) that uses one accelerometer placed at the lower back was proposed [164]. GSI uses autocorrelation coefficients of vertical (\(AR_v\)), frontal (\(AR_f\)), and lateral (\(AR_l\)) accelerations at the location in which the device is attached as the function of time lag \(t\). The sum of positive autocorrelation coefficients of the three axes represent the coefficient of stride cycle repetition (Equation (2.9)) [164]. When \(C_{\text{stride}}\) has the maximum value, the stride time is equal to \(t\). The norm of the autocorrelation coefficients represents the coefficient of step repetition (Equation (2.10)). For a perfect symmetric walking pattern, is assumed that two consecutive steps have the same step time, half of the stride time [164]. GSI is represented as the normalized \(C_{\text{step}}(0.5 \ast \text{Time}_{\text{stride}})\), where the normalized coefficient is \(\sqrt{3}\) since is the maximum value that \(C_{\text{step}}\) can obtain at zero-lag (\(t = 0\)) (Equation (2.11)) [164].

\[
C_{\text{stride}}(t) = AR_v(t) + AR_f(t) + AR_l(t); \text{if} AR(t) < 0, AR(t) = 0
\]

\[
C_{\text{step}}(t) = \sqrt{AR_v(t) + AR_f(t) + AR_l(t)}
\]

\[
GSI = \frac{C_{\text{step}}(0.5 \ast \text{Time}_{\text{stride}})}{\sqrt{3}}
\]

2.4.2 Analysis of Postural Control and Balance

Patients may have balance problems due to neurologic or musculoskeletal disorders. Balance exercises performed as part of a rehabilitation program can help address these problems and can help prevent falls. Physical therapists teach patients static and dynamic balance exercises in both sitting and standing; activities increase in difficulty as balance improves over time. If the patient keeps improving, more complex balance activities can be introduced; such as during walking or standing on compliant surfaces.
Physical therapists use tests to assess patients’ balance. Some common non-instrumented tests used by physical therapists include [28, 96, 44, 79, 126, 149, 17, 69, 21, 31]:

- Romberg Test,
- Limits of Stability Test,
- Single Leg Stance Test (SLST),
- 5 Times Sit to Stand (STS) Test,
- Functional Reach Test (FRT),
- Clinical Test of Sensory Interaction and Balance (CTSIB),
- Timed Up and Go (TUG) Test,
- Tinetti Test,
- Berg Balance Scale (BBS), and
- BESTest.

These tests have semi-objective components; by using rating scales, scores and timed performance, however, they lack objective data. This yield to the use of instruments that can objectively measure the subject’s locomotion quantitatively. By combining both techniques, researchers can conduct these tests by using instruments, such as the Romberg Test or Limits of Stability Test with force platforms, in order to have a complete assessment with both components: rating scales/scores and quantitative data about the subject’s locomotion.

Force platforms are the most common sensor for instrumented balance assessment. They quantitatively measure center of pressure and center of mass displacement of a subject while the subject is standing on the force platform performing static and/or dynamic tasks, such as Romberg Test. The problem with force platforms is that they are often expensive and are not portable.
Researchers have begun to integrate the use of wearable sensors for balance assessment because they are more portable and less expensive. Non-wearable instrumented tests, such as dynamic posturography, and non-instrumented tests are still the gold standard methodologies to assess balance. They are often used to evaluate performance of the wearable sensors systems. For example, researchers used wearable sensors to measure subject’s balance as they were performing the BBS [136]. Another study determined a smartphone could measure static postural stability and distinguish elderly at risk to fall, and they validated the performance of the smart device using a force platform [71]. Additionally, other balance studies have used wearable sensors during gait activities to provide information about subject’s dynamic balance [141, 68, 91].

2.4.2.1 Postural Sway

A common parameter used by researchers and clinicians in static balance assessment is postural sway. Postural sway is the horizontal movement of the person’s center of mass (CoM) in all directions. Postural sway during quiet stance has helped differentiate age-matched healthy controls from those with early untreated Parkinson’s Disease and helped determine changes with disease progression in early PD [100]. Studies that use IMUs and smart devices vary in terms of where to place the sensor to measure postural sway. The studies in this review vary in terms of the sensor’s location used to measure postural sway. There are some that attach the device to the lower back or lumbar spine [51, 11, 10, 19, 68, 91, 96, 13], while others have the subject hold the device on their chest/ sternum with their dominant hand [120, 71]. The most common measures that describes postural sway are sway area, sway range, sway velocity, and sway jerk.

Sway area approximates the area enclosed by the acceleration path in each axis of movement [104]. Studies vary between enclosing the path with a circle or enclosing the path with an ellipse. In both approaches, the acceleration in both the mediolateral (ML) and anteroposterior (AP) direction can be extracted using the acceleration signal at the X-axis and the
acceleration signal at the Z-axis, respectively. Figure 2.5 shows the typical 'Spaghetti' plot that represents the acceleration sway path using ML and AP planes.

Figure 2.5: Postural sway acceleration in ML and AP planes ('Spaghetti' plot) [104].

The acceleration path can be enclosed using an ellipse fitting or ellipse enclosing algorithms [152]. These algorithms can be difficult to implement with datasets that have a lot of data points. To reduce the size of the problem, researchers often use an approach called convex hull. A convex hull is a subset of points that defines a convex polygon that encloses all the points in the set [152]. The minimum enclosing ellipse for the convex hull is the same as the minimum enclosing ellipse for the set of points (Figure 2.6).

Figure 2.6: Convex hull example [152].
Sway range is the maximum distance between any two points in the accelerometer data [104]. Sway range estimates how wide the acceleration was at a particular assessment time point. It can be calculated in all the different axes using Equation 2.12, where $P_{axis}$ is the set of points in a particular axis [104].

$$Range_{axis} = |\max(P_{axis}) - \min(P_{axis})|$$  

(2.12)

Sway velocity is the velocity at which the trunk sways. Similar to gait velocity, sway velocity can be estimated using abstraction models or by direct integration.

Sway jerk is the smoothness of the trunk sway. One of the first reviews on jerk defined the term as the “rate of change of acceleration” [50]. Flash and Hogan (1985) formulated a mathematical model to predict features of coordination of voluntary human arm movements. More recently, jerk is used in many varied applications including postural sway analysis using sway jerk. Sway jerk is typically calculated for the ML-AP plane using Equation (2.13), where $t$ is the time that the trial lasted and $N$ the size of the set of points of the acceleration signal [104]. Since Equation (2.13) involves integration of time derivatives of acceleration components, it is important to make sure that the signal is clean and does not contain much noise. Dealing with noisy differentiation signal may amplify the noises on the signal to be estimated, leading to difficulty in discerning between noise and the actual signal [40].

$$Jerk_{ML-AP} = \frac{1}{t} \sum_{i=1}^{N-1} \sqrt{(AP_{i+1} - AP_i)^2 + (ML_{i+1} - ML_i)^2}$$  

(2.13)

2.4.2.2 Postural Sway: Asymmetry and Variability

Physical therapists often use Modified Clinical Test of Sensory Interaction and Balance (mCTSIB) when evaluating postural sway [70]. In the mCTSIB, subjects have to complete four trials in four different conditions: eyes open-firm surface, eyes closed-firm surface, eyes open-foam surface, and eyes closed-foam surface. After completing the trials, the physical
therapists calculate the asymmetry and variability between the measurements extracted in the different conditions. The asymmetry and variability extracted from the trials between eyes open vs eyes closed are known as the visual dependence, while the asymmetry and variability extracted from the trials between hard surface vs foam surface are known as the surface dependence.

2.4.3 Analysis of Joint Range of Motion

Range of motion (RoM) is the distance a subject’s joints can be moved in a certain direction and is measured in degrees. The goniometer is an instrument used widely by physical therapists to measure RoM angles [54]. RoM testing is an integral part of any physical therapy examination, and generally RoM is examined before physical therapy treatment begins. RoM testing can be performed on specific joints, and if limited motion is found, the physical therapist determines if the cause is muscle tightness, pain, or tightness of ligaments or tendons [5]. Common RoM angles measured by physical therapists are at the shoulder, elbow, hip, knee, and ankle joints and spine angle/inclination (Figure 2.7).

Figure 2.7: RoM angles measured while squatting [42].

RoM is divided into three main types [5]:

- passive RoM: physical therapist is moving the subject’s joint and no active movement is performed by the subject,
- active assistive RoM: the subject can perform movements but cannot complete it because of pain or muscle weakness; assistance of the physical therapist is needed, and

- active RoM: the subject can perform the movement without manual assistance from the therapist.

One common way to get RoM measurements is to calculate pitch, roll, and yaw angles. Pitch and roll angles can be computed using an accelerometer. A simple way to compute pitch and roll angles is using Equations 2.14 and 2.15, where $\text{Acc}_x$, $\text{Acc}_y$, and $\text{Acc}_z$ are the normalized accelerometer values in the X, Y, and Z axis respectively and $\frac{180}{\pi}$ is used to convert the angles from radians to degrees [121].

$$\text{Roll} = \tan\left(\frac{\text{Acc}_y}{\text{Acc}_z}\right) \times \frac{180}{\pi}$$ (2.14)

$$\text{Pitch} = \tan\left(\frac{-\text{Acc}_x}{\sqrt{\text{Acc}_y^2 + \text{Acc}_z^2}}\right) \times \frac{180}{\pi}$$ (2.15)

However, there is a constraint using this method to extract the angles. These equations, besides being simple, are known to only work for the unrealistic assumption of zero or constant velocity. Additionally, there is no way to calculate the yaw angle (heading). Yaw angle can be measured by rate of gyroscope and magnetometer and not only with accelerometer values [121]. Additionally, roll, pitch, and yaw angles are not widely used in joint analysis in the recent years.

Some studies measure RoM by using unit quaternions and/or Euler angles [92, 29, 151]. A quaternion is a 4-tuple whose primary application is in a quaternion rotation operator that can offer fundamental computational, operational, and/or implementation and data handling over conventional rotation matrices [83]. The problem with unit quaternions is that the four quaternion parameters do not have intuitive meaning, a quaternion must have a unity norm to be a pure rotation, and it is harder to understand [43]. Euler angles are popular since they are easy to understand and use. Certain important functions of Euler angles have
singularities and they are less accurate than unit quaternions when measuring incremental changes over time [43]. However, according to the International Society of Biomechanics (ISB) recommendations, Euler angles are preferred for joint coordinate systems of various upper body and lower body joints for the reporting of human joint motion [159, 160].

Joint coordinate system has been established by the ISB in order to report joint motion. There are two main reasons of why the joint coordinate system has been established: (1) lack of standard reporting for joint motion in biomechanics for human movements, making comparisons among studies more difficult, (2) and the advantage of reporting joint motion in clinically relevant terms, making interpretations easier for clinicians and researchers [159]. The joint coordinate system recommend by the ISB established a Cartesian coordinate system for each of the two adjacent body segments that are defined based on bony landmarks [159]. The system is established for both two cases: fixed body and "floating" or moving body and includes three rotational and three translational components. For joint coordinate systems illustrations, refer to studies by Wu et al. [159, 160].

The location of the sensors depends on which RoM angles are intended to be measured. One study introduced the use of a smartphone mounted to subject's back to measure back inclination while subjects stood up and sat down [96]. Other researchers mounted IMUs to the thighs and shanks to extract Euler angles and measure knee flexion [105]. Kanzler et al. mounted an IMU on a shoe while subjects performed walking exercises to measure ankle joint angles using quaternions [77].

2.4.4 Validation against a Gold Standard

Gold standard methods can be categorized into two types: non-instrumented and instrumented. The non-instrumented gold standard methods in gait, balance, and RoM analysis are composed of subjective assessments, such as the assessments mentioned in Section 2.4.2, whereby experts give a score to the subject based on subjective observation. On the other hand, instrumented gold standard methods in gait, balance, and RoM analysis are the go-
niometer, optoelectronic systems, and force platforms due to the capability of attaining objective data.

2.5 Literature Review Discussion

This chapter discusses the evidence for the use of wearable sensors to enhance gait, balance, and RoM analysis in both research and in clinic. An overview of the most common wearable devices, their technical issues, and the parameters generated to define gait, balance, and RoM was provided. Wearable sensor systems have made it possible to obtain locomotion measurements in real time by placing devices on different parts of the body. Additionally, wearable sensors can be used anywhere to provide less expensive and portable gait, balance, and RoM analysis measurements. The literature on this topic is extensive and it is clearly the trend in developing and improving wearable gait, balance, and RoM analysis systems.

2.5.1 Revealing Features in Population

Researchers perform gait, balance, and RoM analysis using wearable sensors for several purposes including: to reveal features that describe a population, to study changes in patient characteristics over time, and to analyze the effect of interventions. This is possible due to the capability of wearable sensors to provide quantitative and objective measurements of gait, balance, and RoM parameters. People with neurological disorders and the elderly [72, 36, 141, 68, 154, 124, 39] and the elderly [142, 91, 71, 147] are common target populations. Often, the goal of studies that focus on these populations is to assess the efficacy of rehabilitation or pharmacologic interventions or to evaluate falling behavior.

A study of individuals with Alzheimer’s Disease (AD) showed that the number of strides, stride length, stride speed, and stride time extracted from wearable devices served as strong indicators for early diagnosis of AD [72]. Another study showed that, for quiet stance with eyes closed, people with Multiple Sclerosis (MS) have a greater sway acceleration amplitude than healthy controls [141]. Moreover, multiple studies that investigated people with
Parkinson’s disease (PD) have shown that wearable sensor measurements serve as indicators to distinguish between people with PD and healthy subjects and also serve as an assessment of the efficacy of rehabilitation and drug interventions [39, 132, 36, 68, 75, 154].

Research with elderly populations has shown that postural sway parameters, statistical features, such as mean and coefficient of variation, and step length extracted from wearable devices can be used to categorize falling behavior [91]. However, another study of the elderly demonstrated that smart devices are not recommended for regular stance in conditions such as eyes open, eyes closed, and dual task since they demonstrated weak to moderate correlations between the force plate center of pressure and smart device measures. Although, they found that the correlations between the force plate center of pressure and smart device measures were high for semi-tandem, tandem, and single leg stance conditions, showing the possibilities of the use of smart devices to evaluate such conditions [71].

These studies show the ability to perform tele-health rehabilitation to monitor home exercise programs, especially for targeted populations who may have difficulty going to a research laboratory to perform the assessments. Additionally, wearable devices show a high possibility to assess the quality of natural locomotion out in the community. It is important to note that these systems should be validated against gold standard assessments and instruments to show more clinically relevant parameters. Comparing wearable devices to gold standards methodologies proof the feasibility, reliability, and validity of wearable devices for gait, balance, and RoM analysis.

2.5.2 Biofeedback

Researchers have used objective measurements extracted from wearable sensors to provide biofeedback [51, 33]. Biofeedback information can be provided visually, auditorily, and/or tactiley. Visual biofeedback can be difficult when using wearable devices for assessment. However, using smart devices this issue can be addressed since most of the smart devices provide small and portable screens. Additionally, auditory biofeedback can be implemented
in such devices by using earphones, adding the capability of having both types of feedback occurring at the same time. This dual feedback can be used with one portable device and can be very beneficial for patients who benefit from feedback, such as those with Parkinson’s disease [51, 29]. On the other hand, tactile biofeedback systems are designed to provide stimulation to the surface of the skin with electrical signals or vibrations [33]. Tactile biofeedback is not recommended since applying such stimulations can be obtrusive and it can affect subject performance during the assessment; particularly, if they are performing gait, balance or other functional tasks.

2.5.3 Wearable Sensor Technology Validation

It is important to highlight that in gait, balance, and RoM analysis there are gold standard assessments and instruments. These gold standard methodologies are often used to evaluate the performance of parameter quantification when using wearable devices. In balance analysis, a study concluded that there is a strong inverse correlation between the Balance Error Scoring System (BESS) and inertial sensor measurements [120]. However, another study used the BESS and a force platform to validate the use of smart devices and track center of gravity movement of the subject [11, 10]. They found a mean absolute error between 5.87% to 10.42% compared to the force platform measures. On the other hand, a study used the Tinetti Test, BESTest, an optoelectronic system, and a force platform to validate IMUs measurements [19]. They reported correlations between 0.5980 and 0.8658 for static exercises with eyes open or eyes closed when comparing the force platform measurements and the center of mass displacement estimation from the IMUs [19].

In gait analysis, optoelectronic systems and pressure mats are the most common gold standard instruments used to validate wearable sensor measurements. High correlations between pace, postural, rhythm and phases parameters have been documented in the literature. On the other hand, that is not always the case for variability and symmetry measurements. A study conducted a detailed investigation to explain the poor agreement between param-
eters extracted from wearable devices and a pressure mat [57]. The study determined that the poor agreement was due to inherent differences between the two systems rather than an inability of the wearable sensor to measure the gait characteristics [57].

In RoM analysis, a study concluded that although goniometry is a reasonably accurate method to measure joint angles in static situations, it is not precise to measure the angle of catch in individual patients [151]. However, there are studies that have evaluated the validity of IMUs and smart devices to measure joint angles against an optoelectronic system. These studies demonstrate that wearable devices are reliable to measure joint angles, where the error usually ranges between 1–6 [16, 130, 76, 92, 84, 77].

Studies included in this review that validated their results with gold standard methodologies show discrepancies related to assessment of gait, balance, and RoM. Some studies highly recommend the use of wearable sensors to assess balance; others report variable and not as strong results. However, they introduced the possibilities for future use of wearable devices and suggest potential improvements. Additionally, these results highlight the importance of caution when selecting a reference system for validation studies. Validity is important since it will help ensure that researchers truly measure gait, balance, and RoM in an accurate and objective manner.

2.5.4 Machine Learning in Gait, Balance, and RoM

Machine learning has been playing an important role in gait, balance, and RoM analysis in recent years. Machine learning techniques can be used to quantify gait, balance, and RoM parameters [46, 166, 41, 30, 109], distinguish between populations and conditions [93, 116, 115, 9], and estimate assessments scores [147, 129]. The techniques used in the literature showed the efficiency of machine learning to reduce and create gait, balance, and RoM parameters. Machine learning has the capability to converge to global optimum, even in non-linear datasets. Additionally, studies in this review that used machine learning techniques showed the highest accuracy, 88%–99%, for both parameter quantification and
population/condition classification. Moreover, recent studies showed that gait and balance assessments scores, such as Berg Balance Score and Tinetti Test Scores, can be estimated by using features extracted from wearable devices and machine learning models [147, 129].

However, the amount of data from different subjects and the time needed to train the algorithms in order to have a reliable and accurate model is immense. Additionally, most of the research builds classification models focused on a binary classification, healthy versus non-healthy, limiting the adaptability and reliability for different targeted population. Also, the selection of features might be constrained by the number of subjects that participate in the study [129]. At last, when using models based on activities from gold standard assessments, the person needs to perform all the activities in which the model was constructed. Therefore, the model may not be feasible in a free living environment due to that some activities may be difficult to perform in such environment [147].

2.5.5 Limitations

Some of the studies included in this review had similar limitations: small sample size, lack of description of inclusion/exclusion criteria, and data loss was not reported. Additionally, there were studies that did not provide sufficient information about the protocols followed to perform assessments, making it difficult to make comparisons among studies. A limitation of the studies is that the results presented mostly represent the use of wearable sensors in controlled environments or laboratory settings. Furthermore, most of the studies did not include a long-term follow-up assessment. Research in work and home environments as well as long-term follow-up studies are needed in order to consider the use of wearable sensor technologies to assess gait, balance, and RoM in daily life. By monitoring activities of daily living, early detection of walking deviations and assessments of the ability of an individual to live independently in their community will be more complete, reliable, and correlated to individual’s usual behavior. Another limitation is that optimum sensor locations to extract gait, balance, and RoM parameters are still inconclusive due to the variety of locations used
in the literature. This affected the level of obtrusiveness in some studies since they used multiple devices attempting to get as much reliable data as possible. Knowledge of the most optimal sensor locations will help future research to reduce processing power and energy consumption needed to extract gait, balance, and RoM parameters. Furthermore, this will also decrease the level of obtrusiveness. If obtrusiveness is minimized, it may not interfere with trial results as much since the subjects may feel more comfortable participating in the trial.
Chapter 3: A Comparison of Smartphones and Inertial Measurement Units for Measuring Gait

According to the literature reviewed in Chapter 2, IMUs are the most common wearable sensor used in gait analysis\(^2\). However, IMUs do not have to be standalone sensors, but are often integrated into other wearable or smart devices as discussed in Chapter 2. According to the Pew Research Center, more than 77% of people in the United States have access to applications that use these embedded sensors [26]. To determine which of the two (i.e., standalone IMUs versus a smartphone with an embedded IMU) shows the most promise for this research, we conducted a study to compare the performance of gait analysis using Shimmer3 IMUs and a Nexus 6 Android smartphone [163]. Our study was based on the work proposed in [122, 95], that describes a system using smartphone sensors to detect steps, differentiate between left and right foot, and calculate path deviation.

3.1 Methodology

Figure 3.1 shows the study methodology, as explained in the following sections.

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3.1.1 Data Collection

3.1.1.1 Participants

Seven healthy young adults (five males and two females) voluntarily participated in this study. The participants were between 19 and 25 years old and 1.524–1.829 meters (5–6ft) in height. One participant suffered an accident and injured her right knee before the study was performed, but willingly continued in this study.

3.1.1.2 Procedure and Instrumentation

Five Shimmer3 IMUs [8] were attached to both thighs and calves and on the lower back of each participant, alongside a Nexus 6 Android smartphone attached at the lower back (Figure 3.2).

Figure 3.2: Clinical gait comparison sensor placement [163].

The participants performed three different tests: straight path test, deviation test, and impediment test. The number of steps performed by the participants in each test were visually noted as the baseline number of steps for further evaluation. Below the description of the tests performed:

- Straight Path Test: In the straight path test, the participants were asked to walk in a straight line at their normal pace. This test adopts the walkway used in a gait assessment test called the Functional Gait Assessment (FGA) [157]. FGA is a clinical
gait assessment based on the Dynamic Gait Index (DGI) assessment, where the goal of DGI is to assess the risk of falling while performing a series of gait exercises [158]. However, a problem with the DGI is its subjectivity, relying upon the visual observation of the therapist. The FGA assessment improves the DGI by defining new quantifiable parameters, such as deviation [157]. To perform the FGA, the walkway shown in Figure 2.3 was used, where participants started at the center of the walkway and, depending on the deviation from the center, a level from 0 to 3 was assigned. Level 0 is the best possible outcome, indicating no deviation occurred during the exercise. Deviation level depended on how much the participant deviated: 15.24 centimeters (cms) for level 1, 25.4 cms for level 2, and 38.1 or more cms for level 3.

• Impediment Test: The impediment test assesses the proposed system’s ability to distinguish between normal and abnormal gait by testing for pronounced differences between the left and right steps of a person’s gait. To simulate an impediment, participants wore a knee brace on either the right or left leg. The knee brace is used since knee braces have been shown to provide a realistic simulation of impediments and limits a participant’s ability to perform a full knee extension [48, 14]. Each participant walked the 6.096 meters path established in the FGA test three separate times: one without the impediment, one with the brace on the right leg, and one with the brace on the left leg.

• Deviation Test: Deviation tests were performed also using the walkway shown in Figure 2.3. Two types of deviation tests were performed:

  - Deviate and Keep Straight Test: Participants were asked walk at the center of the walkway, and to continue walking while deviating up to a certain level; at that point, participants were to stay on that level until they reached the end of the walkway. This test was performed three times, one per each deviation level, where the participant chose to either deviate to the right side or to the left side.
– *Deviate and Go Back Test*: This test follows the same procedure as the Deviation and Keep Straight test, with the exception that in this test, participants were asked to go back to the center from the level of deviation before reaching the end of the walkway.

Figure 3.3 shows sample trajectories taken by the participants while performing the deviation tests, where trajectory $A$ represents a *Deviate and Go Back* test and trajectory $B$ represents a *Deviate and Keep Straight* test.

![Sample deviation test trajectories](image)

Figure 3.3: Sample deviation test trajectories, where trajectory (A) represents a Deviate and Go Back test and trajectory (B) represents a Deviate and Keep Straight test.

3.1.2 Pre-Processing

Pre-processing deals with several issues that are present when working with five wearable sensors. One issue arising from our data collection setup is that the number of the samples collected from each IMU may not be the same; one sensor could gather a different number of samples than another sensor on the same test. There may also be occurrences when the sensors have different data ranges. For example, one sensor may be able to record values up to 9.8 $m/s^2$, whereas another one may be able to record up to 10.1 $m/s^2$ at the same position. In order to compare these data appropriately, these problems are addressed using interpolation and normalization. Additionally, when using signals from five different IMUs, they need to be processed to fuse them into a single signal. We describe the techniques used for interpolation, normalization, and fusion below:
• Interpolation: The signals from the collected data need to have the same amount of data points to make calculations easier. A linear interpolation function was applied to compensate for changes in clock drifts between sensors, while maintaining the same information gathered from the tests.

• Signal Fusion: Each IMU returns three signals per sensor (movement information along the $x$, $y$, and $z$ axes), providing a total of fifteen signals. To fuse these signals, their magnitude is calculated per sensor (Equation 2.1). The resultant signal magnitudes are used for step segmentation, step classification, and path deviation.

• Normalization: After the data vectors are interpolated and fused, the data are normalized to improve consistency using Equation 3.1 to have the same $y$-axis range, where $Scale = 20$ and $Translation = 10$. A scaling factor of 20 scales the output range from the default normalization range $[0, 1]$ to $[0, 20]$, and the translation factor of 10 moves the output after scaling from $[0, 20]$ to $[-10, 10]$.

$$Value_{new} = \frac{Value_{old} - Min}{Max - Min} \times Scale - Translation \quad (3.1)$$

3.1.3 Step Detection

To detect and count the number of steps, traditional peak detection and accelerometer-based step detection are used. In traditional peak detection, peaks of the $y$-axis values of the accelerometer sensor are detected using a moving window, which are saved as a step of a fixed length. A modified accelerometer-based algorithm is used to calculate the energy and the bias of the accelerometer data [103]. Using the energy and bias, the algorithm creates an average moving window. Steps are detected when a high peak is followed by a low peak within the search window [122, 95]. In our study, steps are detected per IMU, and the most frequently detected number of steps are obtained.
3.1.4 Step Segmentation and Differentiation

The role of the step segmentation module is to extract the normalized magnitudes from each step. This step uses the peak locations extracted in the step detection module, where the values between locations $L_{i-1}$ and $L_i$ belong to the signal for step $i$.

3.1.5 Step Classification

The goal of the step classification module is to classify which steps are right or left steps. This module makes this decision by using the slopes from the segmented rotation vector data. The slopes can be found by the values at the beginning and the end of the segmentation. If the slope is positive, then this indicates that the step is left; a negative slope, on the other hand, means that the step is right [122, 95]. It is important to distinguish between right and left steps to be able to identify any problems associated with a specific side of the body.

3.1.6 Deviation Calculation

In many of the tests, the participant walks following a straight path, and the system checks whether the participant deviates from the center of the path. Using the step length of the participant and the trunk angle extracted from the rotation vector sample from each step, the system can quantify this deviation, $D_i$, for step $i$ using Equation 2.7 (Figure 2.4). After the deviation for each step is calculated, the cumulative deviation is calculated using Equation 2.8. This is performed to check the total deviation from the starting point to the ending point [122, 95].

3.2 Evaluation of the Case Study

The evaluation of the above approaches was performed using the data obtained from the smartphone, using one IMU at the location of the smartphone, and using all five IMUs.
3.2.1 Step Detection

The accuracy of step detection module was evaluated by calculating the root-mean-square error (RMSE) of the number of steps detected ($p_i$) versus the real step count ($g_i$) using Equation 3.2. A similar step count between these two values leads to a RMSE closer to 0. When using the traditional peak detection algorithm, RMSE values were 5.7966, 3.4829, and 4.2240 for smartphone, one IMU, and five IMUs, respectively. On the other hand, using the modified algorithm [122, 95], RMSE values were 2.3428, 2.0377, and 1.4779 for smartphone, one IMU, and five IMUs, respectively. Figure 3.4 shows a sample result when using the modified algorithm with five IMUs. Each point represents the starting/ending point of the step detected.

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (p_i - g_i)^2}{N}} \tag{3.2}
\]

![Figure 3.4: Step detection example result [163].](image)

Overall, using five IMUs for step detection provides the lowest RMSE of 1.4779. This indicates that the step count produced by the system sometimes counts one step either more or less than the real number of steps performed by the participant. Additionally, it is clear
that better results are obtained using the algorithm presented in [122, 95] compared to the traditional peak detection algorithm.

3.2.2 Step Segmentation and Differentiation

Figure 3.5 shows the step segmentation results, where each curve describes the signal of an individual segmented step. The system with five IMUs provides more defined segmented steps compared with the smartphone-based system and the system with one IMU. With five IMUs, it is easier to segment and differentiate the steps because the starting and ending points of each step are relatively the same. This happens because the system has more information about the walking pattern of the participant. On the other hand, when using a smartphone, the starting points from each step are more separated, so deciding when each step begins is more difficult.

![Figure 3.5: Step segmentation and differentiation: X-axis: percentage of completion, Y-axis: normalized acceleration values [163].](image)

3.2.3 Step Classification

Figure 3.6 shows the results of the step classification module in a trial where the subjects performed ten steps. The number of steps classified for each side should be either equal, if the subject took an even number of steps, or off by one, if the subject walked an odd number of steps. In this trial, the smartphone-based system did not detect three steps and the IMU-based systems did not detect one step. Further, the system using one IMU also misclassified six steps. Odd steps (steps 1, 3, 5, 7, and 9) were performed with the left leg.
and even steps (steps 2, 4, 6, and 8) were performed with the right. The system using one IMU misclassified steps 4 and 8 as left steps, as they were supposed to be classified as right steps, and steps 3, 5, 7, and 9 as right steps, as they were supposed to be classified as left steps. Incorrectly classified steps occurred because the classification depends on the slope of the signal. Using a smartphone and five IMUs, the signals of the steps are either increasing (positive) or decreasing (negative) overall. However, using one IMU, the decreasing and increasing portions of the signals are often equally distributed, making it more difficult to calculate the appropriate slope of the signal.

![Graph showing step classification with X-axis: percentage of completion, Y-axis: rotation values](image)

Figure 3.6: Step classification: X-axis: percentage of completion, Y-axis: rotation values [163].

3.2.4 Deviation Detection

Step deviation accuracy is computed as the ratio of correctly classified levels over the complete set of trials. A level is correctly classified if the subject deviates to a certain level and the system detects it accordingly. All systems achieved 100% accuracy for the straight path tests and impediment tests. However, with 95% confidence level, 33.33% ± 18.86%, 41.67% ± 19.72%, and 29.17% ± 18.19% accuracy were achieved in the deviation tests for smartphone-based, one IMU, and five IMUs, respectively. We note that the deviation detection algorithm depends on the trunk rotation of the subject. Some of the subjects may have not rotated the trunk as much as expected when deviating from the center of the walking path, causing the system to not detect the deviation. Further, the system showed the worse results with five IMUs because the algorithm used to calculate the deviation only
takes in consideration a single device placed in the trunk and not multiple devices placed in different locations.

### 3.3 Conclusions of Case Study

This case study compared the performance of a gait analysis system using smartphone sensors and IMUs. Experimental results showed that the gait analysis system with five IMUs provides the best performance in step detection, with improved accuracy when segmenting and classifying steps. This is because with five IMUs, more information about the walking patterns of the subject are provided. However, the five IMU-based system showed the worst performance in the step deviation module because the algorithm used to calculate the deviation only takes in consideration the information provided by a single sensor placed in the trunk.

Future research should consider other locations to place the sensors and improve the methodology to process the signals. Additionally, validation of the methodology against a gold standard system is needed to demonstrate the reliability of wearable sensors to assess gait and balance. Furthermore, a bigger population and more gait spatiotemporal parameters are needed to present more useful information regarding gait and balance.
Chapter 4: Step Length and Width Estimation Using Wearable Sensors

This chapter presents a follow-up study to the work discussed in Chapter 3\(^3\). In this chapter, we propose novel methods to measure two gait parameters, step length and step width, using wearable sensors. Step length and step width help determine if a person’s walking pattern is symmetrical and if it shows balance disorders. Spatial asymmetry is present when the step length of the feet are unequal. On the other hand, changes in step width are seen in people with balance problems and when people walk faster. Usually, people that walk faster tend to decrease their step width, while people that have a balance disorder tend to increase their step width to compensate the loss of balance [59].

4.1 Methodology

This study follows a similar approach as the case study presented in Chapter 3. It consists of data collection, preprocessing, step detection, step segmentation, and step length and step width estimations. Figure 4.1 depicts all phases of this methodology, which will be explained in the following sections.

Figure 4.1: Step length and step width estimation flow diagram [41].

4.1.1 Data Collection

A total of four participants took part in the data collection process. The group consisted of three males and one female, ages 24–25, with heights varying between 1.643–1.798 meters (5.39ft–5.9ft). Given the outcome of our first study which showed promise for the use of multiple IMUs, we placed five Shimmer3 IMU sensors [8] on each participant, four placed on both thighs and calves and one in the lower back (Figure 4.2). The data extracted from the IMUs consisted of 3D acceleration (accelerometer), 3D angular velocity (gyroscope), and 3D magnetic field (magnetometer). Additionally, the participants’ leg lengths were manually measured.

![Sensor locations during data collection](image)

Figure 4.2: Sensor locations during data collection [41].

Data was collected using the Computer Assisted Rehabilitation ENvironment (CAREN) [7]. CAREN is equipped to extract continuous motion capture and force plate data. Three participants walked on the treadmill two times set up at different speeds, 0.8 \( m/s \) and 1.2 \( m/s \), with a duration of 90 seconds each. The other participant only performed the 1.2 \( m/s \) trial due to time constraints. Four reflective markers placed in both heels and both toes were used for motion capture. The data extracted from CAREN was used to generate the ground truth. Figure 4.3 shows an example of a trial being performed by a participant.
4.1.2 Preprocessing

Data was pre-processed following an identical approach presented in Chapter 3 (i.e., interpolation, signal fusion, and normalization), with identical parameters for each pre-processing step.

4.1.3 Step Detection

Following the modified accelerometer-based step detection algorithm presented in Chapter 3, three-axial accelerometer data is used to calculate the energy and the bias of the signal. The samples are analyzed depending on the state of the algorithm and steps are detected when a high peak is followed by a low peak within a search window. The algorithm returns the starting ($L_{i-1}$) and ending ($L_i$) locations in the signal of that step.

To detect the steps using the data collected with CAREN, peak detection was performed in the $y$-axis data gathered by both force plates using Matlab, where each peak detected represents a heel-strike.
4.1.4 Step Segmentation

Step event locations found in the step detection module were used to extract segments representing each step in the walking magnitude signal. The first four and last four segments were discarded to eliminate the steps performed in the acceleration and deceleration phases as the treadmill started and stopped. After discarding the first and last steps, a total of 1,121 step segments were recorded across all seven trials performed.

The ground truth of the steps was generated using the marker locations extracted from the CAREN motion capture sensors. Step length and step width were defined as the distance between the left and right heel markers at heel-strike in the $z$-axis and $x$-axis coordinated, respectively.

4.1.5 Step Length and Step Width Estimations

4.1.5.1 Step Length Estimation

After steps were segmented and ground truth was generated, six features were extracted from each segment: walking frequency, acceleration variance, leg length, maximum normalized walking magnitude value, minimum normalized walking magnitude value, and mean normalized walking magnitude value. Walking frequency, acceleration variance, and leg length were selected based on previous studies reviewed in Chapter 2 [36, 137]. Maximum, minimum, and mean normalized walking magnitude values are introduced to quantify the reaction of the acceleration when a step is performed.

We developed a deep neural network architecture to estimate the step length. Different network topologies were investigated when building the neural network and the one with the best accuracy was selected. The selected topology consisted of two fully connected hidden layers, where the first hidden layer has five neurons and the second hidden layer has three neurons. All layers used a sigmoid function as the activation function. The inputs of the
network are the features previously mentioned. Figure 4.4 visually represents the network used to estimate step length.

![Neural network topology used to estimate step length.](image)

To train the network, a learning rate of 0.2 and momentum of 0.1 were used. The learning rate is the parameter used to adjust the weights of the network with respect to the loss function used. Momentum is used to avoid getting stuck in a local minima and never reaching the global minima and smooth the variations. The dataset used to train and test the network consisted of all six extracted features and the step length value generated from CAREN, labeled as the expected, with a total of 1,121 instances that represented the steps. 80% of the data were used as the training set and 20% of the data were used for testing. This will help to evaluate the network with data not seen before, avoiding misleading and optimistic results.

4.1.5.2 Step Width Estimation

As there are not many equations based on measuring step width with wearable devices, the Pythagorean theorem was taken into consideration to estimate the step width (Figure 4.5).
To calculate the step width, Equation 4.1 is introduced. Step width ($SW$) is estimated using the step length ($SL$) previously calculated, multiplied by the tangent of the angle created from the center of the body and the foot by which the step was performed ($\theta$). The angle, $\theta$, is obtained from the rotational yaw angle of the IMU placed at the calf attached to the leg by which the step was executed. Because this only calculates half of the step width, the result of that calculation is multiplied by two.

$$SW = 2 \times SL \times \tan(\theta)$$  \hspace{1cm} (4.1)

### 4.2 Evaluation and Discussion of Step Length and Step Width Estimation

The evaluation metric used in this study was the mean absolute error (MAE). MAE is calculated using Equation 4.2, where $p_i$ is the predicted value, $g_i$ is the real value extracted from CAREN, and $N$ is the number of steps.

$$MAE = \frac{\sum_{i=1}^{N} |p_i - g_i|}{N}$$  \hspace{1cm} (4.2)

The deep neural network architecture developed in this study achieved a MAE of 0.2396 cm when predicting the step length value. This value indicates that the neural network had a great performance measuring step length. However, it is known that the results of the deep neural network architecture might slightly vary when more data from new participants is collected.
are obtained and included in the network. Additionally, future research has to take into consideration the location of where the wearable devices are placed since the neural network was trained with data extracted from the devices at the locations selected in this study; hence, if a device is changed from position or orientation, re-training needs to be performed.

On the other hand, a 2.53 cm MAE was achieved by the step width estimation algorithm. This value indicates that the step width estimation algorithm had a fair performance, showing the need for more research to improve the accuracy of step width estimation with wearable devices. It is believed that the results of the step width estimation algorithm were affected by the way the angle, \( \theta \), was calculated. In some cases, the rotational yaw angle extracted from the sensor did not represent the expected created angle.

Besides the results achieved by the methods proposed in this study, it was noticed that the step length is affected by the treadmill velocity. As shown in Figure 4.6, it can be seen that at higher speeds, the step length tends to be higher.

![Figure 4.6: Average step length vs velocity [41].](image)

For the next study for this work, the work should focus on extracting more spatiotemporal parameters from a greater number of subjects. Additionally, another pre-processing technique should be followed in order to improve the results presented in this study and in the case study presented in Chapter 3. For example, the use of filtering techniques might be useful to clean some of the noise presented by the raw signals. Additionally, extracting parameters such as stance phase, swing phase, and velocity will help us to better understand
why the participant stepped longer or shorter. This information will also help to describe in more detailed the gait characteristics of the participants.
Chapter 5: Measure Gait Spatiotemporal Characteristics in Multiple Sclerosis

Multiple Sclerosis (MS) is an autoimmune, neurodegenerative disease associated with progressive demyelination in the central nervous system that affects at least 2.5 million people worldwide [38]. MS causes differing symptoms in individuals depending on the areas of demyelination; however, at least 85% of affected individuals report balance and walking impairments that, over time, lead to increased walking disability and participation restrictions. Researchers have demonstrated that, even individuals with short MS disease duration and little observable disability, may walk slower, take shorter steps, and have prolonged step time. Prior research also shows increased time spent in double limb support and less time in swing phase of gait compared to healthy control subjects [56].

Instrumented gait analysis has grown as a useful tool to measure and evaluate movement disorders, such as the ones present in individuals with MS, since clinical rating scales, like the MS Walking Scale, provide only semi-quantitative data, and cannot assess gait characteristics in detail or describe how this changes over time [66]. Therefore, this chapter assesses wearable sensor’s reliability to measure gait in MS against an instrumented walkway system. This chapter addresses the main drawbacks presented in the previous two studies by:

- collecting data from a bigger population,
- proposing new accurate pre-processing techniques, and
- extracting more spatiotemporal characteristics from the wearable sensor signals.

Additionally, this study validates the methodology against a gold standard system to ensure the reliability of wearable sensors to assess gait and balance.
5.1 Data Collection

5.1.1 Participants

Twenty-four females with MS (EDSS$^4$ 3.0-6.0) participated in this study. Participants were between 30 to 75 years old, 152–178cm (4.99–5.84ft) in height, and 49–160kg (108–352.7lbs) in weight. All participants gave informed consent to participate in this study, and the study was approved by the university Institutional Review Board (IRB) #Pro00038089.

5.1.2 Procedures and Instrumentation

Spatiotemporal gait parameters were examined for each participant using six body worn inertial sensors: one positioned on the top of each foot, one on each wrist, one over the sternum and one over L1 (Mobility Lab Opals, APDM Inc., Portland, OR) while the participant walked on a 26 foot (7.93M) long walkway system containing embedded electronic pressure activated sensors (Figure 5.1) (Zeno Mat, Protokinetics Walkway System, Protokinetics LLC, Havertown, PA). Each participant completed 12 walking trials; 6 trials at their self-selected, comfortable walking speed and 6 trials at their fastest possible walking speed. Participants were closely supervised by a physical therapist and were allowed to rest as needed during the gait assessment. Each trial consisted of walking at either a comfortable or fast pace inside a pre-defined walk path of 10.36 meters in length and 1.22 meters in width, where the first and last 1.22 meters were used for acceleration and deceleration. Both systems were linked together using the timestamps stored after data was collected. The instrumented walkway system was used as the laboratory reference for gait characteristics in this study. This system also includes a video camera to videotape participants as they walked on the gait mat. Participants signed a consent for videotaping.

$^4$The Expanded Disability Status Scale (EDSS) is a method of quantifying disability in multiple sclerosis and monitoring changes in the level of disability over time. It is widely used in clinical trials and in the assessment of people with MS.” Definition sourced from https://mstrust.org.uk/a-z/expanded-disability-status-scale-edss.
Figure 5.1: Data collection sensor locations; red represents the back of the silhouette, and blue represents the front of the silhouette.

5.2 Methodology: Processing of Raw Data

5.2.1 Preprocessing Signal

Each accelerometer sensor within the wearable devices can provide three-dimensional information when recording. The use of multiple sensors providing multiple signals can make analysis of raw gait data challenging. Figure 5.2 depicts the different pre-processing methods that were applied to the multiple signals obtained from the different sensors.

Figure 5.2: Data pre-processing flowchart.

To retain only a single acceleration signal per device, the magnitude of the acceleration of the devices placed on the feet were calculated using Equation 2.1. Figure 5.3 illustrates the resulting signal. This maintains the orientation to avoid misalignment issues.
Once the acceleration magnitudes of the devices on both feet were calculated, the magnitudes were inverted (Figure 5.4). Inverting the signals reduces the complexity of detecting peaks in the signals that are at different heights.

After the magnitudes were inverted, the signals were filtered using two filtering techniques. The first filtering technique is the Savisky Golay filter, which reduces high frequency noise and reduces low frequency signals using differentiation to increase the precision of data without altering the signal tendency [98]. The Savisky Golay window used in this study was equal to 29 samples. This window was selected based on multiple iterations of trying multiple window sizes. Figure 5.5 shows the filtered signal.
The filtered signal is passed to the second filter – that is, applying the exponential weighted moving average (EMA). EMA is calculated using Equation 5.1, where \( \alpha \) is the weight applied to the signal, and \( EMA_0 = Golay_0 \). The \( \alpha \) value used in this study is 0.05. Figure 5.6 shows the resulting signal.

\[
EMA_i = \alpha \times Golay_i + (1 - \alpha) \times EMA_{i-1} \tag{5.1}
\]

The filtered signals were then normalized using Equation 3.1, where scale is equal to \(- \text{min}(EMA)\) and the translation value was ignored. This yielded resulting signals where the
y-axis ranged between 0 and the distance between the $\min(EMA)$ and $\max(EMA)$. Figure 5.7 shows the resulting signal.

Figure 5.7: EMA filtered magnitude to the normalized magnitude.

5.2.2 Stride and Step Detection

After the signals are pre-processed, an algorithm was built to detect peaks in the pre-processed signals. These peaks estimate the moment in which the participant is starting the swing phase of each stride. First, the location of where the signal drops in the pre-processed signal is detected. Using this location as a starting point, the algorithm is designed to locate the first high peak within a defined window. The values of this window were selected based on normative values of healthy individuals in a study by Latorre et al. [88]. According to their work, the mean ± standard deviation of stride time in healthy participants is between 1.08 and 1.19 ± 0.09–0.12 seconds [88]. Knowing that these values can be affected by gait speed and the condition of the individual, we expanded the window to 650ms and 1550ms to consider subject individual differences. Once the first high peak is detected, the starting point of the window is shifted to the location of where the last peak was detected, and the process is repeated until all peaks are processed. Figure 5.8 shows the peaks detected using this technique.
Figure 5.8: Peaks detected in normalize magnitude.

After all peaks are detected, the algorithm validates the peaks detected. The reason for this validation is that there are some cases where at the end of the peak selection, only one low peak is selected since it will be the highest peak of the last window. The last peak is validated using the height of the previous selected peaks. If the absolute difference between the average height of the previous selected peaks and the last peak in the last window is higher than a threshold, then the last peak is a low peak. The threshold value is 2 units ($m/s^2$) based on research performed on the pre-processed signals of each individual in this study. The low peak was removed from the chosen peaks. Figure 5.9 shows an example of a case where a low peak was detected but it was removed by this validation.

Figure 5.9: Validating last peak detected.
Once the stride locations were detected, spatiotemporal parameters were calculated for each stride. To detect the locations of where stance and swing phase occurred, a similar approach for stride detection was used with a few modifications:

- instead of using a filtered magnitude, the filtered accelerometer signal along the z-axis was used, and

- instead of looking for high/positive peaks, low/negative peaks were detected.

Figure 5.10 shows the negative peaks detected along the filtered accelerometer z-axis. These peaks represent the end of a swing phase and beginning of a stance phase (heel-strike).

![Figure 5.10: Negative peaks along the filtered accelerometer z-axis.](image)

With heel-strike locations and foot-flat locations detected previously, we designed another algorithm to detect toe-off location. This algorithm used an EMA-filtered accelerometer x signal and a window of five samples (39 ms) that is between each foot-flat location and the end of the swing location. A linear regression was calculated within the window. The window is moved forward between locations until the slope of the linear regression is greater than zero and the angle that the line creates with respect to the x-axis is greater than 30 degrees. The slope indicates the trend of the signal at that moment in time, such that zero slope represents a constant (no trend), negative slope represents that values are decreasing.
(negative trend), and positive slope represents that values are increasing (positive trend). The angle indicates the incline of the slope. An angle exceeding 30 degrees indicates that the signal is inclined enough to represent movement of the sensor, hence, the person is moving forward. Once these conditions were fulfilled, the last index/location used in the window represents the location of where toe-off happens, hence, the location of the start of swing phase. The process was repeated until all locations were processed.

Using the heel-strike and toe-off locations, swing and stance phase gait parameters, such as swing time, stance time, swing phase percentage of gait cycle, and stance phase percentage of gait cycle, were calculated, where $ts$ is the timestamp at a specific location:

\[
Swing_{time} = ts_{\text{heel} - \text{strike}_i} - ts_{\text{toe} - \text{off}_i} \tag{5.2}
\]

\[
Stance_{time} = ts_{\text{toe} - \text{off}_i} - ts_{\text{heel} - \text{strike}_{i+1}} \tag{5.3}
\]

\[
Duration = Swing_{time} + Stance_{time} \tag{5.4}
\]

\[
Swing_{phase} = \frac{Swing_{time}}{Duration} \times 100 \tag{5.5}
\]

\[
Stance_{phase} = \frac{Stance_{time}}{Duration} \times 100 \tag{5.6}
\]

Step time is the time elapsed between the first contact of a foot and the following first contact of the opposite foot. Step time is calculated by subtracting the first contact timestamp of the opposite foot from first contact timestamp of the foot being evaluated. Cadence is the rate at which a person walks, expressed in steps per minute. To approximate cadence, Equation 5.7 is used, where $mean_{step\text{time}}$ is the mean of the step times in the trial expressed in seconds and 60 is the number of seconds in a minute. To obtain step length, we re-trained the network topology used in Chapter 4 due to the fact that we changed the location of the sensors [41].

Velocity is the distance travelled in a certain period of time. Velocity can be used to determine functional outcomes since it is correlated with functional ability and balance.
Using the step times and step lengths previously calculated, velocity was obtained by dividing step length \( SL_i \) by its respective step time \( ST_i \)

\[
Cadence = \frac{60}{\text{mean}_{\text{step time}}}
\]  

(5.7)

5.3 Evaluation

Between method differences were analyzed using the intra-class correlation coefficient (ICC) for consistency (two-way mixed) and mean differences. ICC is a widely used reliability index in reliability analyses [82]. ICC reflects the degree of correlation and agreement between measurements. Scatter of between-method differences is reported as the standard deviation (SD) and the 95% limits of agreement (LoA).

Differences of comfortable speed trial means and fast speed trial means were explored with dependent paired \( t \)-tests. Alpha was set to 0.05 for all analyses. Additionally, coefficient of variance as percentage of mean and 95% confidence limits are reported for all methodologies.

Between-method consistency was determined for all comfortable and fast walking trials obtained from simultaneous recordings with Mobility Lab wearable sensors and with the instrumented walkway system. The purpose of this analysis was to determine the accuracy of and correlations between the three methods. Mobility Lab showed excellent between-method consistency for step time and cadence with ICC > 0.9 and good between-method consistency for velocity and stride length with an ICC between 0.79 and 0.9 for both comfortable and fast trials. The proposed methodology in this study showed excellent between-method consistency for step time, cadence, velocity, and step length with ICC > 0.9 for both comfortable (Table 5.1) and fast trials (Table 5.2). Mobility Lab reported stride length instead of step length since the latter is not provided by the software.

On the other hand, Mobility Lab showed low between-method consistency for gait cycle phases with ICC < 0.31 for both comfortable and fast trials. Moreover, the proposed method gait cycle phases showed good between-methods consistency at comfortable walking speed.
Table 5.1: Between-method consistency for comfortable trials against Protokinects.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>ICC</th>
<th>Mean Difference</th>
<th>95% LoA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step Time (s)</strong></td>
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<td></td>
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<tr>
<td>Proposed</td>
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<td>-0.0011</td>
<td>0.0062</td>
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<td>Mob. Lab</td>
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<td>0.0014</td>
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<td></td>
<td></td>
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<tr>
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<tr>
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<td>1.2322</td>
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<tr>
<td><strong>Phases (%GCT)</strong></td>
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<td></td>
<td></td>
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<tr>
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<tr>
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<tr>
<td><strong>Velocity (cm/s)</strong></td>
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<td></td>
<td></td>
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<tr>
<td>Proposed</td>
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<td><strong>Step Length</strong></td>
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<tr>
<td>Proposed</td>
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<tr>
<td>Mob. Lab</td>
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<td>0.0508</td>
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</table>

Table 5.2: Between-method consistency for fast trials against Protokinects.

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<th>Mean Difference</th>
<th>95% LoA</th>
</tr>
</thead>
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<td></td>
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<tr>
<td>Proposed</td>
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<td>Mob. Lab</td>
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<td>-0.0018</td>
<td>0.0054</td>
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<tr>
<td><strong>Cadence (steps/min)</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>2.7826</td>
</tr>
<tr>
<td>Mob. Lab</td>
<td>0.9982</td>
<td>0.3760</td>
<td>1.1519</td>
</tr>
<tr>
<td><strong>Phases (%GCT)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>0.2936</td>
<td>1.3069</td>
<td>6.3437</td>
</tr>
<tr>
<td>Mob. Lab</td>
<td>0.2982</td>
<td>4.3189</td>
<td>3.3702</td>
</tr>
<tr>
<td><strong>Velocity (cm/s)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>0.9985</td>
<td>0.6247</td>
<td>2.5489</td>
</tr>
<tr>
<td>Mob. Lab</td>
<td>0.8845</td>
<td>12.1736</td>
<td>5.8167</td>
</tr>
<tr>
<td><strong>Step Length</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>0.9990</td>
<td>0.0631</td>
<td>0.8273</td>
</tr>
<tr>
<td>Mob. Lab</td>
<td>0.8269</td>
<td>0.1135</td>
<td>0.0503</td>
</tr>
</tbody>
</table>

with ICC = 0.7680, but low between-methods consistency at fast walking speed with ICC < 0.3.

Despite the inconsistencies observed in the between-method comparisons for certain gait parameters, the between-trial speed comparisons when performed separately for all three methods demonstrated similar results except for gait cycles phases and velocity for Mobility.
Lab (Table 5.3). Additionally, evidence was shown that the population performed significantly different between comfortable and fast trials since $t$-test showed a $p$-value lower than 0.0001 for all the parameters (Table 5.4).

Table 5.3: Description of gait pathology in MS.

<table>
<thead>
<tr>
<th></th>
<th>Comfortable Walk</th>
<th></th>
<th>Fast Walk</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>CoV</td>
<td>95% Limits</td>
<td>Mean</td>
</tr>
<tr>
<td>Proto</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step time (s)</td>
<td>0.5473</td>
<td>1.93%</td>
<td>0.0218</td>
<td>0.4872</td>
</tr>
<tr>
<td>Cadence (steps/min)</td>
<td>110.7128</td>
<td>1.96%</td>
<td>4.4924</td>
<td>124.1755</td>
</tr>
<tr>
<td>Swing (%GCT)</td>
<td>33.7324</td>
<td>1.48%</td>
<td>1.0303</td>
<td>35.3599</td>
</tr>
<tr>
<td>Stance (%GCT)</td>
<td>66.1498</td>
<td>0.75%</td>
<td>1.0303</td>
<td>64.6401</td>
</tr>
<tr>
<td>Velocity (cm/s)</td>
<td>110.0608</td>
<td>3.73%</td>
<td>8.5036</td>
<td>138.0823</td>
</tr>
<tr>
<td>Step Length (cm)</td>
<td>59.3768</td>
<td>2.67%</td>
<td>3.2818</td>
<td>66.4206</td>
</tr>
<tr>
<td>Mobility Lab</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step time (s)</td>
<td>0.5459</td>
<td>1.97%</td>
<td>0.0221</td>
<td>0.4890</td>
</tr>
<tr>
<td>Cadence (steps/min)</td>
<td>111.0204</td>
<td>1.95%</td>
<td>4.4825</td>
<td>123.7994</td>
</tr>
<tr>
<td>Swing (%GCT)</td>
<td>38.1880</td>
<td>1.24%</td>
<td>0.9760</td>
<td>39.6793</td>
</tr>
<tr>
<td>Stance (%GCT)</td>
<td>61.8124</td>
<td>0.76%</td>
<td>0.9759</td>
<td>60.3212</td>
</tr>
<tr>
<td>Velocity (cm/s)</td>
<td>100.5444</td>
<td>3.93%</td>
<td>8.1729</td>
<td>125.9087</td>
</tr>
<tr>
<td>Stride Length (cm)</td>
<td>1.0810</td>
<td>2.85%</td>
<td>0.0637</td>
<td>1.2149</td>
</tr>
<tr>
<td>Proposed</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step time (s)</td>
<td>0.5484</td>
<td>1.95%</td>
<td>0.0221</td>
<td>0.4890</td>
</tr>
<tr>
<td>Cadence (steps/min)</td>
<td>109.4193</td>
<td>1.91%</td>
<td>4.3145</td>
<td>122.4418</td>
</tr>
<tr>
<td>Swing (%GCT)</td>
<td>34.0280</td>
<td>1.43%</td>
<td>1.0037</td>
<td>36.6668</td>
</tr>
<tr>
<td>Stance (%GCT)</td>
<td>65.9720</td>
<td>0.74%</td>
<td>1.0037</td>
<td>63.3332</td>
</tr>
<tr>
<td>Velocity (cm/s)</td>
<td>109.6490</td>
<td>3.73%</td>
<td>8.4590</td>
<td>137.4576</td>
</tr>
<tr>
<td>Step Length (cm)</td>
<td>59.3341</td>
<td>2.69%</td>
<td>3.2998</td>
<td>66.3603</td>
</tr>
</tbody>
</table>
Table 5.4: Paired $t$-test results.

<table>
<thead>
<tr>
<th></th>
<th>Mean Difference</th>
<th>$t$</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Protokinetics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step time (s)</td>
<td>0.0601</td>
<td>-11.1384</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Cadence (steps/min)</td>
<td>-13.4626</td>
<td>-12.3862</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Swing (%GCT)</td>
<td>-1.6275</td>
<td>-12.8094</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Stance (%GCT)</td>
<td>1.6275</td>
<td>12.8094</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Velocity (cm/s)</td>
<td>-28.0214</td>
<td>-11.1384</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Step Length (cm)</td>
<td>-0.1409</td>
<td>-9.1127</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td><strong>Mobility Lab</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step time (s)</td>
<td>0.0569</td>
<td>10.9327</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Cadence (steps/min)</td>
<td>-12.779</td>
<td>-11.5347</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Swing (%GCT)</td>
<td>-1.4914</td>
<td>-8.9727</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Stance (%GCT)</td>
<td>1.4912</td>
<td>8.9671</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Velocity (cm/s)</td>
<td>-25.3642</td>
<td>-11.071</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Stride Length (cm)</td>
<td>-0.1339</td>
<td>-9.3785</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td><strong>Proposed Method</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step time (s)</td>
<td>0.0594</td>
<td>11.4625</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Cadence (steps/min)</td>
<td>-13.0225</td>
<td>-12.611</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Swing (%GCT)</td>
<td>-2.6388</td>
<td>-5.9411</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Stance (%GCT)</td>
<td>2.6388</td>
<td>5.9411</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Velocity (cm/s)</td>
<td>-27.8086</td>
<td>-10.8647</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Step Length (cm)</td>
<td>-7.0262</td>
<td>-9.1577</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

5.4 Discussion

We evaluated the reliability of gait analysis in people with MS using a wearable sensor system (Mobility Lab) against an instrumented walkway system (ProtoKinetics). Additionally, we proposed a new method to transform raw data obtained from the wearable sensors into gait spatiotemporal parameters. The reliability of the proposed method was evaluated against data collected using the instrumented walkway system. One main finding was that we
were able to accurately determine gait spatiotemporal parameters using raw data generated from wearable sensors. Specifically, we were able to use our proposed method to accurately calculate gait parameters in subjects with MS using raw data generated from the Mobility Lab wearable sensors. A second main finding was that there was consistency among the three methods of determining gait spatiotemporal parameters. The Mobility Lab generated gait parameters and those generated using the raw data were consistent with the Protokinetics instrumented walkway system generated gait parameters. Another main finding was that the proposed method using raw data may have improved accuracy of measurement of gait spatiotemporal parameters velocity and phases with wearable sensors. As seen in Table 5.1 and 5.2, the mean difference between the proposed methods and Protokinetics for velocity and phases were lower than 0.63 and 1.31, respectively, for both comfortable and fast walk trials. On the other hand, the mean difference between Mobility Lab and Protokinetics for velocity and phases were higher than 9.50 and 4.30, respectively, for both comfortable and fast walk trials. However, minor improvements to the proposed methods are needed to divide the gait cycle phases, especially at high speeds.

We collected data using wearable sensors and the walkway system simultaneously at comfortable and fast gait speeds, thus simplifying comparison of the two systems. To compare the systems, between-method consistency and parameter means were analyzed and reported. No major differences in consistency were found for both methods when measuring step time and cadence. The proposed method also did not show major differences in consistency when measuring velocity and step length. However, the between-methods consistency for gait cycle phases showed minor differences in the proposed method in comfortable trials, but low consistency in fast trials. This means that regarding spatiotemporal parameters of gait in people with MS, speed may compromise measurement accuracy. Some factors that might have affected accuracy may have been manual synchronization, wearable sensor misalignment, low filtering parameters, and/or more signal noise introduced in fast speed trials.
For both Mobility Lab and the proposed method, near perfect agreement (ICC > 0.99) was seen for step time at both comfortable and fast gait speeds, reflected in absolute mean differences lower than 0.0018 seconds. There was also near perfect agreement for cadence at both gait speeds, reflected in absolute mean differences lower than 0.3760 steps per minute. Meanwhile, the ICC of cadence for the proposed method achieved excellent agreement for both gait speeds, reflected in absolute mean differences lower than 1.7337. Low agreement (ICC < 0.3018) was seen for gait phases for Mobility Lab at both gait speeds, reflected in absolute mean differences around 4.5% of Gait Cycle Time (GCT). However, for the proposed methods moderate agreement was seen for gait phases at comfortable speeds and low agreement at fast speeds. This re-validates the statement that accuracy of spatial measures are speed-dependent [133, 123]. The proposed method showed near perfect agreement for step length at both gait speeds, reflected in absolute mean difference lower than 0.0631 cm. Studies suggest that comparing step/stride length is more reliable at comfortable speeds [133, 81]. However, the use of machine learning techniques to measure step length in the proposed study showed that step/stride length can be reliable at fast speeds.

Determining the difference between gait measures at different speeds is important when assessing gait and balance in people with MS [32]. All of the systems showed that there is still a significant difference in gait parameters for the MS population with EDSS lower than 6.0 compared to norms for healthy individuals. Subjects in this study walked relatively fast, but took around 13 more steps per minute and spent about 2% less time in stance phase of gait compared to their comfortable walk.
Chapter 6: Conclusions and Future Work

This work pertains to the implementation of a wearable sensor methodology to assess gait and balance, particularly to assist with the quantitative assessment of walking quality among those with walking disorders. As described in Chapter 1, key challenges associated with this effort are enumerated as follows:

1. **Efficiency**: A wearable sensor-based approach must efficiently operate in real-time to have quantifiable impact on clinical recommendations and outcomes.

2. **Interperson Variations**: The developed system should successfully handle the complexity of analyzing signals from different individuals.

3. **Data Pre-processing and Denoising**: Data must be processed and cleaned, and algorithms for sensor alignment and signal fusion from multiple sensors should be reliable and accurate.

To tackle these challenges, we detailed four key research contributions, including

1. experimentally evaluating and exposing differences between smartphones and inertial measurement units for assessing gait,

2. proposing new methods to estimate step length and step width using wearable sensors,

3. proposing new methods to process raw signals, and

4. assessing wearable sensor’s reliability to measure gait.

These contributions stemmed from three research studies. In the first study, we compared the performance of a gait analysis system using smartphone sensors and standalone IMUs.
Experimental results showed that the gait analysis system with several (five) IMUs was most accurate at step detection and segmentation. However, this system also showed the worse performance in computing step deviation, as the algorithm used to calculate the deviation only considers the information provided by a single sensor placed in the trunk.

In a follow-up study, we proposed novel methods to measure the gait parameters, step length and step width, using five wearable sensors, as inspired by our first study. A deep neural network was developed to measure step length, and a new algorithm was introduced to calculate step width. The study used features, such as walking frequency, acceleration variance, leg length, and the maximum, minimum, and mean normalized walking magnitude value, as inputs of the network to estimate the step length. This study extended our first by improving the accuracy of step length estimation from past researches and by taking on the challenge to estimate step width using wearable sensors, which is limited in the literature.

The third study evaluated the reliability of gait analysis for patients diagnosed with Multiple Sclerosis of the wearable sensors system, Mobility Lab, against a walkway system, ProtoKinetics. Additionally, the study proposed new methods to transform raw data from wearable sensors to gait spatiotemporal parameters. One main finding was that MS did not affect measurements of gait spatiotemporal parameters by wearable sensors, indicating that wearable sensors can be used to clinically evaluate individuals without compromising accuracy. Another main finding was that the proposed methods improved measurements of gait spatiotemporal parameters with wearable sensors compared to Mobility Lab measurements. However, minor improvements are needed to divide the gait cycles phases, especially at high speeds.

This work has three main limitations. The first limitation is the fair accuracy of some gait parameters such as step width. Future studies can take advantage of machine learning algorithms to estimate gait parameters to improve the accuracy and validity of gait measures using wearable sensors. Another limitation is presented when evaluating fast speed trials. Other future studies can focus on the mitigation of noise when participants walk at a higher
speed. Finally on a clinical side, this work did not present a post-training evaluation of the participants after training is completed. It is intended to re-evaluate the population to see if there are significant changes in gait measures after the population completes training.
References


[70] Linda B Horn, Teresa Rice, Jennifer L Stoskus, Karen H Lambert, Elizabeth Dannenbaum, and Matthew R Scherer. Measurement characteristics and clinical utility of the clinical test of sensory interaction on balance (ctsib) and modified ctsib in individuals with vestibular dysfunction. *Archives of physical medicine and rehabilitation*, 96(9):1747–1748, 2015.


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