UNIVERSIDAD POLITÉCNICA DE MADRID
Escuela Técnica Superior de Ingenieros de Telecomunicación

Enhancing gait assessment in assistive technologies for the Visually Impaired integrating inertial sensors

DOCTORAL THESIS

Submitted for the degree of Doctor by:

Karla Miriam Reyes Leiva
Biomedical Engineer, M.Sc. in Engineering and Science of Materials

Madrid, 2024

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I dedicate this doctorate to the women in my life whose stories inspired me to challenge social paradigms and pursue my academic dreams: Grandma Elena, Grandma Dilcia, and Aunt Chepita. But above all, I want to dedicate it to the living example I had at home; my mother. Mom, I owe everything to you. Thanks to you, I learned to fly.

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Abstract

This doctoral thesis is a compendium of scientific articles that explores the application of assistive technology for visually impaired people, with a specific focus on enhancing gait assessment through the integration of inertial sensors. The research comprises a compendium of five articles, each contributing to the improvement of gait analysis and, ultimately, mobility and independence for visually impaired individuals. Key findings from the research include the potential of IMU sensors in various assistive technologies for visually impaired people, the development of a low-cost motion measurement system for gait analysis and orientation and mobility training, the accurate estimation of gait parameters using wearable inertial sensors, the use of computer vision for machine interaction, and the effectiveness of LSTM-based models in predicting gait parameters. The thesis makes original contributions by exploring the potential of low-cost IMU sensors in rehabilitation, advancing gait parameter estimation, and bridging the gap between research and real-world applications. Future directions for research include the further refinement of the low-cost motion measurement system, longitudinal studies to assess the long-term effectiveness of proposed solutions, investigation of deep learning algorithms for other applications, and the continued integration of user-centered design principles in developing assistive technologies. This research not only highlights the possibilities of assistive technology for visually impaired individuals but also lays the groundwork for future innovations that can empower them to navigate the world with greater confidence and autonomy.

Resumen

Esta tesis doctoral, es un compendio de artículos científicos que explora la aplicación de la tecnología de asistencia para personas con discapacidad visual, con un enfoque específico en mejorar la evaluación de la marcha a través de la integración de sensores inerciales. La investigación comprende un compendio de cinco artículos, cada uno contribuyendo a la mejora del análisis de la marcha y, en última instancia, la movilidad y la independencia de las personas con discapacidad visual. Los hallazgos clave de la investigación incluyen el potencial de los sensores IMU en varias tecnologías de asistencia para personas con discapacidad visual, el desarrollo de un sistema de medición del movimiento de bajo costo para el análisis de la marcha y la formación en orientación y movilidad, la estimación precisa de parámetros de la marcha utilizando sensores inerciales portátiles, el uso de visión por computadora para la interacción con máquinas y la efectividad de los modelos basados en LSTM para predecir parámetros de la marcha. La tesis realiza contribuciones originales al explorar el potencial de los sensores IMU de bajo costo en rehabilitación, avanzar en la estimación de parámetros de la marcha y cerrar la brecha entre la investigación y las aplicaciones del mundo real. Las futuras direcciones de la investigación incluyen el perfeccionamiento del sistema de medición del movimiento de bajo costo, estudios longitudinales para evaluar la efectividad a largo plazo de las soluciones propuestas, la investigación de algoritmos de aprendizaje profundo para otras aplicaciones y la integración continua de principios de diseño centrados en el usuario en el desarrollo de tecnologías de asistencia. Esta investigación no solo destaca las posibilidades de la tecnología de asistencia para personas con discapacidad visual, sino que también sienta las bases para futuras innovaciones que puedan capacitarlas para navegar por el mundo con mayor confianza y autonomía.

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Abbreviations and acronyms

VIP Visually Impaired People

ADL Activity of Daily Living

AFB American Foundation of the Blind

AI Artificial Intelligence

BLE Bluetooth Low Energy

CNN Convolutional Neural Networks

CSV Comma-separated values

D Total Displacement

EKF Extended Kalman filtering

ETAS Electronic Travel Aids

FCN Fully Convolutional Network

FN False negative

FP False positive

GPS Global Positioning System

GV Gait Velocity

HAR Human Activity Recognition

HH Hand Height

IAPB International Agency for the Prevention of Blindness

IC Image-based product Classification

IMU Inertial Measurement Unit

KF Kalman fILTER

LL Leg Length

LSTM Long Short-Term Memory

MD Mean Difference

MLP Multi-Layer Perceptron

MSE Mean Square Error

MSVI Moderate to Several Visual Impairment

OGA Observational Gait Analysis

OCR Optical Character Recognition

OMC Optical Motion Capture

PA Postural Assessment

QoL Quality of Life

RNA Robotic Navigation Aid

RV Real Value (RV)

SC Step Count

SD Standard Deviation

SL Step length

SSD Sensory Substitution Device

SZ Safety Zone

UVM Unmanned Vending Machines

VIO Visual Inertial Odometry

VM Vending Machines

VRT Voice Recognition Technology

WBU World Blind Union

WHO World Health Organization

Chapter 1

Introduction

1.1 Vision Impairment

More than 2.2 billion individuals worldwide are confronted with vision impairments, and a substantial proportion of them, numbering at least 1 billion, have vision impairments that could have been mitigated or even remedied through appropriate interventions[1]. The World Health Organization (WHO) provides a comprehensive framework for understanding visual impairment, characterizing it as the partial or complete diminishment of the capacity to perceive visual stimuli. This broad classification further delineates visual impairment into two key categories, namely, distance and near vision impairment. In alignment with WHO's definition, a vision impairment occurs when an ocular condition disrupts the optimal functioning of the visual system and subsequently compromises one or more of its core visual faculties[187]. Such conditions have implications for affected individuals, accentuating the significance of advancements in the field of assistive technologies to ameliorate their daily lives.

Visual impairment is a condition that warrants thorough examination to gauge its extent and implications. A common method for such assessment involves the evaluation of visual acuity, a specific metric in ascertaining the degree of visual deficiency[187]. This evaluative process systematically categorizes the severity of visual impairment into several groups, encompassing mild vision impairment, moderate vision impairment, severe vision impairment, outright blindness, and near vision impairment. The categorization of visual impairment according to these gradations provides a comprehensive framework for understanding the range of visual problems.

However, the assessment of visual impairment extends mere visual acuity, especially in clinical contexts. Health professionals often undertake more examination that encompasses an array of additional visual functions[187]. These evaluations are instrumental in obtaining a comprehensive state of an individual's visual health and capacity. They encompass critical parameters such as the field of vision, contrast sensitivity, and color vision. Each of these parameters, while distinct, is a fundamental aspect in a person's visual impairments and provides insights for the development of some interventions and assistive technologies.

1.1.1 Causes and Statistics

Visual impairment, a complex and multifaceted issue, arises from a variety of underlying causes, each contributing to the global burden of this condition[188]. Through statistical analysis, we can gain valuable insights into the prevalence of these contributory factors. Cataracts are responsible for approximately 6.32% of the overall burden of visual impairment, while glaucoma, accounts for 6.9% of the burden. Furthermore, conditions such as trachoma, diabetic retinopathy, unaddressed refractive error, and unaddressed presbyopia are also components, contributing 0.19%, 0.29%, 12%, and a substantial 80.12% to the burden, respectively[188]. These statistics serve as a reminder of the intricate factors that contribute to visual impairment, encompassing structural and functional aspects alike.

The impact of visual impairment is not uniformly distributed across populations, with a range of demographic and socio-economic factors coming into play[1]. Notably, people residing in rural areas, those with limited incomes, older members of society, individuals with disabilities, ethnic minorities, and indigenous populations are often burdened by eye conditions and vision impairment. This discrepancy is primarily rooted in the inadequate integration of eye care services within broader healthcare systems[1]. This systemic misalignment underscores the urgent need for a comprehensive approach that ensures equitable access to eye care.

In 2020, a comprehensive assessment of the global landscape of visual impairment revealed the extent of this issue[188]. It was estimated that 237 million individuals suffered from significant distance vision impairment, with women constituting 55% of this affected population. Also, a substantial majority of these people, a significant 89%, resided in low and middle-income countries where access to adequate eye care remains a pressing concern[188]. There is a need for interventions and strategies to alleviate the global burden of visual impairment, particularly in underserved regions.

Blindness, a condition characterized by severe visual impairment, is not a uniform entity but rather a spectrum that considers both the depth of visual loss and the extent of central visual field constriction[191]. The legal framework introduces the concept of being "legally blind," a pivotal reference point that involves precise criteria[191]. To meet this legal threshold, an individual's central visual acuity must not exceed 20/200 in the better eye, even with the most effective corrective measures. Alternatively, it relies on the measurement of visual field constriction, which should not exceed twenty degrees[191]. This intricate approach recognizes the diverse nature of visual impairments and their profound effects on a person's visual perception. It highlights that an individual can be legally classified as blind, even if they retain minimal visual perception, such as the ability to perceive light. This legal framework emphasizes that the extent of visual impairment encompasses intricate aspects of visual perception and function, extending beyond the binary presence or absence of sight.

The realm of visual impairment statistics is marked by a fundamental challenge, primarily rooted in the intricate task of estimation. Accurately quantifying the prevalence of blindness, especially on a global scale, needs a reliance on statistical approximations to yield data with substantive relevance[192][193]. As an illustrative example, within the context of the United States of America, estimations from 2017 provided a glimpse into the landscape of visual impairment, suggesting the existence of approximately 1 million individuals grappling

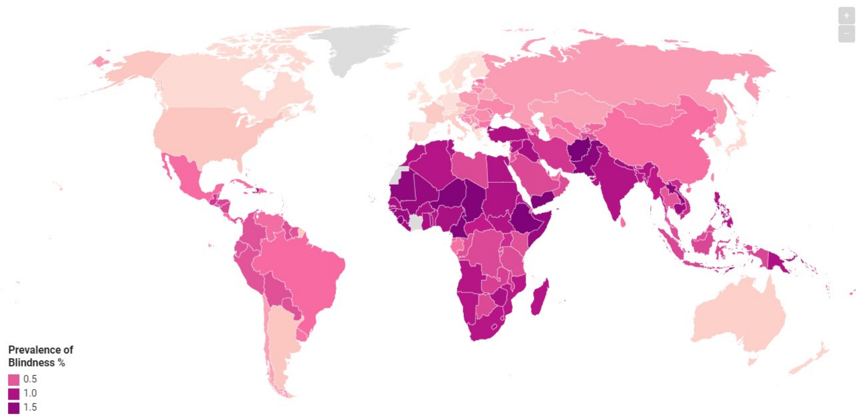

Figure 1.1: Age-standardised and crude prevalence of blindness by country Source: IAPB Vision Atlas / LESH

with the burden of blindness. These projections were accompanied by a 95% uncertainty interval, thoughtfully designed to encompass the full spectrum of variability inherent in such estimations[192][193]. Furthermore, the extensive expanse of Geographical Europe serves as a home to an estimated populace that surpasses 30 million people, each wrestling with various degrees of visual impairment, ranging from the challenges of blindness to the subtler constraints of partial sightedness[189]. Though undoubtedly informative, this remarkable figure draws attention to the formidable obstacles encountered when endeavoring to obtain precise and comprehensive statistical insights within the realm of visual impairment.

To shed light on the global distribution of visual impairment, the International Agency for the Prevention of Blindness (IAPB) has endeavored to create a comprehensive map delineating the prevalence of blindness and moderate to severe visual impairment (MSVI) by country. This visual representation, depicted in Figure 1.1, serves to observe the global variability in the prevalence of visual impairments, highlighting the importance of continued research and intervention efforts in this domain. The process of estimation and data collection remains an ongoing pursuit, vital in enhancing our understanding of the worldwide impact of visual impairment (Figure 1.2).

Visual impairment establishes a compelling and intricate nexus with various other health conditions, thereby contributing to the appearance of a multifaceted and challenging health problem. As posited by Burton and colleagues [190], this interrelation can be thoughtfully classified into three causal categories, as illustrated in Figure 1.3:

Firstly, it is crucial to acknowledge that the presence of a vision impairment serves as a catalyst for the onset or exacerbation of various other health conditions. This intricate interplay can manifest through diverse mechanisms, including injury-induced complications, diminished healthcare accessibility, constraints on physical activity, or heightened social isolation.

Furthermore, it is noteworthy that many risk factors associated with vision impairment are not exclusive to this condition but are commonly shared with a range of other issues. Notable examples encompass factors such as smoking, poverty, restricted access to healthcare services,

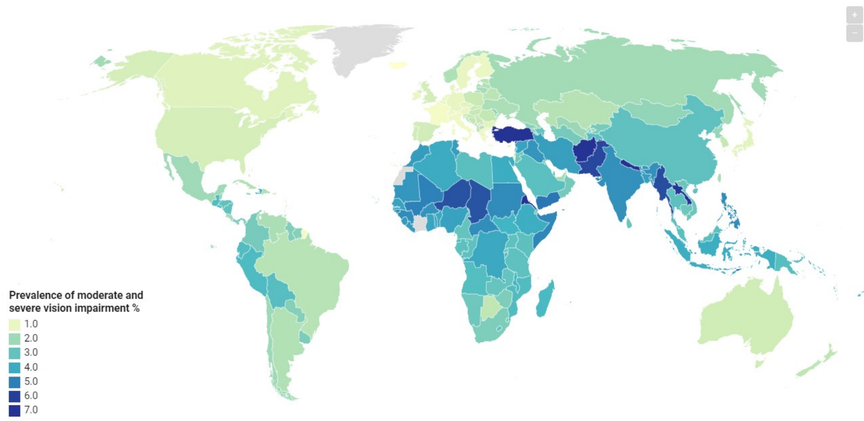

Figure 1.2: Age-standardised and crude prevalence of moderate to severe visual impairment (MSVI) by country Source: IAPB Vision Atlas / LESH

the natural process of aging, or suboptimal dietary habits. A global perspective reveals that systemic health problems of considerable magnitude, such as diabetes, cancer, and dementia, possess the capacity to exert detrimental effects on ocular health [190]. This, in turn, not only curtails accessibility to vital eye health services but also culminates in the development of vision impairment. Thus, the web of interconnected health conditions amplifies the significance of addressing and mitigating the multifaceted challenges associated with vision impairment.

The repercussions of vision impairment are extensive, profoundly influencing an individual's overall quality of life. This effect manifests in the form of considerable obstacles encountered when attempting to carry out routine daily tasks, thereby introducing complexity to the execution of even the most fundamental activities [114]. Furthermore, the ramifications extend to the realm of social interactions, rendering participation in communal activities intricate and demanding. The ability to secure and sustain gainful employment, a cornerstone of self-sufficiency and economic well-being, becomes a subject of uncertainty and concern.

However, the impact of vision impairment is not restricted only to these tangible and immediate challenges. It expands by augmenting the risk of a range of additional health problems. This expanded spectrum encompasses psychological conditions such as depression and anxiety, exerting a significant toll on an individual's emotional and mental well-being. Moreover, it amplifies the likelihood of physical consequences, including an increased susceptibility to falls and injuries, which further compound the complexities associated with this condition[190].

In the last three decades, a noticeable reduction in the worldwide prevalence of blindness and vision impairment has been observed [**?**]. This promising trend does not negate the existence of a substantial burden associated with avoidable blindness that persists to this day. Consequently, it is imperative to acknowledge that considerable challenges remain and need our attention and concerted efforts. To meaningfully address this enduring burden, there is an evident imperative for intensified endeavors aimed at both the prevention and treatment of avoidable blindness. This emphasis is particularly salient within the context of low- and middle-income countries, which are disproportionately impacted by this issue[194].

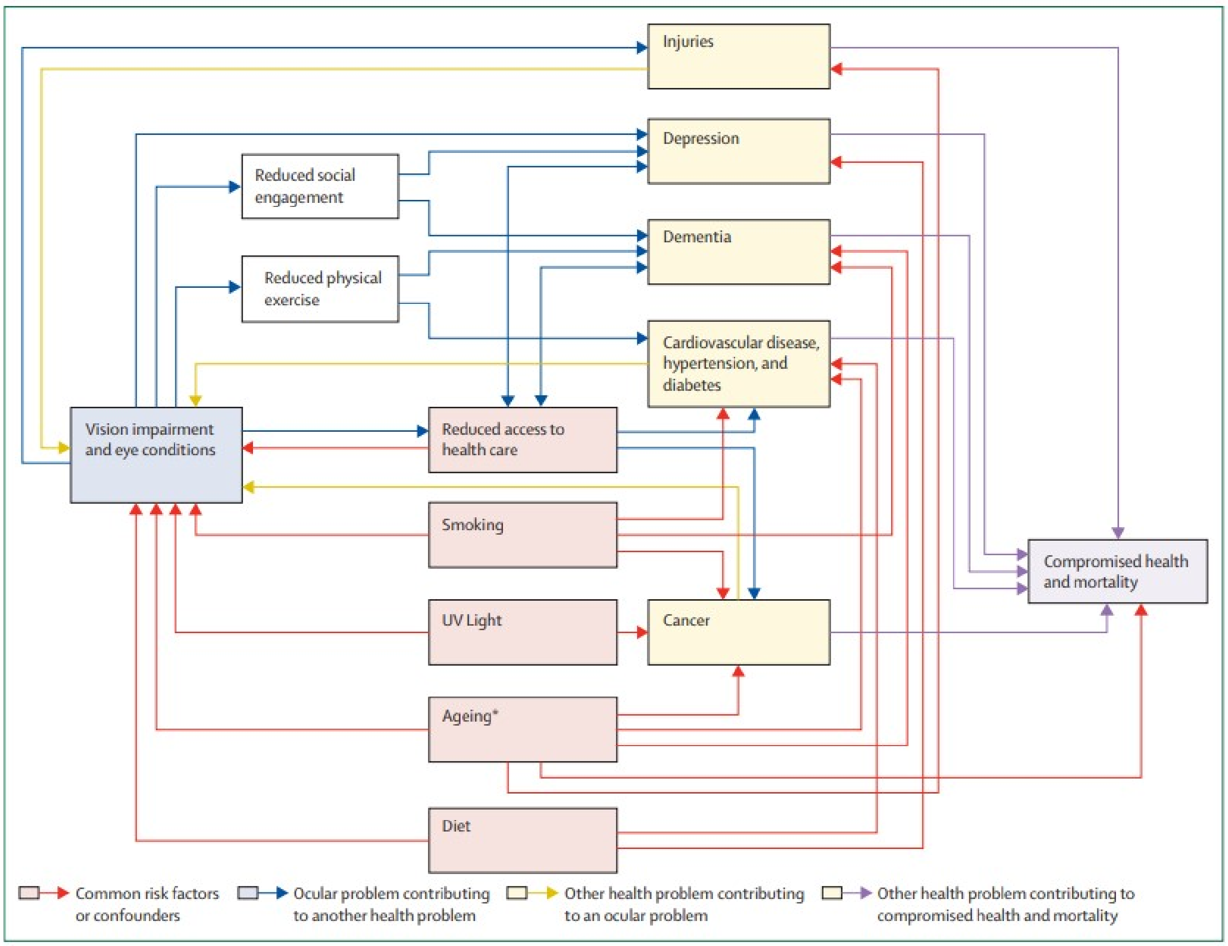

Figure 1.3: Relationships between vision impairment and general health. Source: The Lancet Global Health Commission on Global Eye Health

1.1.2 Rehabilitation of visually impaired people

In situations where a person is congenitally affected by a visual impairment or experiences vision loss due to an injury or illness, it's necessary to initiate a comprehensive rehabilitation process designed to address their specific needs and challenges. This restorative journey seeks to provide the necessary support and interventions tailored to their unique circumstances, enabling them to regain a sense of independence and functional ability within their daily lives.

Rehabilitation for people with visual impairments encompasses a structured and systematic training process meticulously designed to equip them with the essential skills and resources indispensable for the proficient execution of their daily activities. The overarching goal of this rehabilitation process is to empower VIP, enabling them to actively engage in a multitude of environmental settings while fostering self-sufficiency within their newly acquired state of blindness. It is imperative to note that this training is meticulously delivered by a team of dedicated specialists and professionals, who offer a tailored, one-on-one approach that is closely attuned to the unique needs and circumstances of each individual undergoing rehabilitation [118]. This personalized guidance is crucial for facilitating an effective and comprehensive journey toward independence and enhanced quality of life for people with visual impairments.

Rehabilitation plays a significant role in equipping VIP with the tools and capabilities necessary to surpass the challenges posed by their vision loss. The ultimate objective of rehabilitation is to empower VIP, enabling them to lead lives characterized by independence and fulfillment. This multifaceted process is instrumental in facilitating the development of a diverse skill set and the acquisition of knowledge [118], thereby arming them with the proficiency required to excel in various domains. An example of such proficiency encompasses mastering the usage of assistive technologies and acquiring the skills needed for safe navigation within their surroundings effectively[196].

On a global scale, rehabilitation programs have been thoughtfully designed to cater to the diverse needs of people with visual impairments, delivering a spectrum of assistance services. These programs are typically categorized into three key domains, each tailored to address unique circumstances: Residential Rehabilitation Programs, Community-Based Rehabilitation Programs, and Home-Based Rehabilitation Programs. The scope of services provided varies in accordance with the capacities and resources of each program[143].

According to the comprehensive analysis outlined in the prior report from the World Rehabilitation Study in 2016, specific services have emerged as prominent in terms of their incidence and impact. Foremost among these services is the indispensable training in orientation and mobility, which is pivotal for empowering individuals with the skills to move confidently and independently within their environment. Additionally, rehabilitation programs frequently extend services focused on activities of daily living (ADL) and self-care, emphasizing the cultivation of essential life skills. Another important facet of rehabilitation offerings is the service of adaptation to blindness, guiding individuals in adjusting to their changed visual condition[143].

Moreover, a subset of rehabilitation programs ventures further, contributing to professional development and the utilization of cutting-edge technologies to re-force the self-sufficiency and well-being of those with visual impairments[134]. These programs, tailored to meet the multifaceted needs of individuals, play a crucial role in facilitating their reintegration into society and enhancing their overall quality of life.

The insights derived from the extensive study carried out by the World Blind Union (WBU) and the American Foundation for the Blind (AFB), as delineated in the comprehensive report of the World Rehabilitation Study [143], provide a noteworthy perspective on the prevalence and emphasis of O&M training within rehabilitation programs. This investigation encompassed a wide geographical scope, enlisting the participation of 48 countries spanning Asia, Europe, Latin America, North America, and the Caribbean.

A key revelation stemming from this study is the pervasive integration of O&M Training into the overarching framework of rehabilitation programs. This service is strategically incorporated into different categories of rehabilitation programs, aligning with the distinctive characteristics and requirements of each. Notably, in the realm of Home Rehabilitation programs, O&M Training stands as a universal component, with a resounding 100% inclusion rate. Within Residential Rehabilitation programs, constituting an essential element of rehabilitation services, O&M Training maintains a substantial presence, being encompassed within 85% of such programs. Likewise, the report highlights that Community-Based Rehabilitation programs, designed to cater to the unique needs of individuals within their communities, prominently feature O&M Training, with an impressive inclusion rate of 94%.

These findings underscore the significance attributed to O&M Training as an integral facet of rehabilitation programs, acknowledging its important role in equipping VIP to navigate their surroundings confidently and independently[134]. This comprehensive approach ensures that they receive the necessary support to enhance their quality of life and foster their inclusion in society.

The aforementioned global rehabilitation study determines the need to improve two important aspects of rehabilitation programs:

1. Limited human, technological, and financial resources. Although rehabilitation training is supervised by public or private organizations, all countries reported the need for more resources to expand and improve, or develop and initiate rehabilitation services. The first critical aspect brought is the limitations in the availability of essential resources—namely, human resources, technological infrastructure, and financial backing. While the administration and oversight of rehabilitation training typically fall under either public or private organizations, the prevailing consensus across all surveyed nations underscores the indispensable requirement for augmented resources[143].

2. Transportation and geographic limitations. These factors impact the provision of rehabilitation services and access to them, especially for users in rural areas. Another critical dimension that emerges is the confluence of transportation and geographic limitations and their pervasive influence on the delivery and accessibility of rehabilitation services. The intricate interplay between these two factors profoundly affects both the provision of rehabilitation services and the ability of users, particularly those residing in rural regions, to access these services[143].

In the rehabilitation programs, interdisciplinary rehabilitation programs are essential for people with visual impairments. Interdisciplinary rehabilitation helps to improve the quality of rehabilitation of VIP by preventing, reducing, or compensating for their visual impairments in daily life [197]. These programs combine the expertise of multiple disciplines, such as ophthalmology, optometry, physical therapy, occupational therapy, and psychology, and the mobility and autonomy training to provide comprehensive care and support. The importance and basic need for Mobility Training for Personal Autonomy is emphasized [195], his training teaches VIPs how to navigate their environment safely and independently. It includes instruction on using a white cane, guide dog, or other mobility aid, as well as training on how to orient themselves to their environment and use public transportation. So as the importance of immersion training [198] this training involves placing VIPs in real-world situations to help them practice their new skills and build confidence. In addition to mobility training and immersion training, interdisciplinary rehabilitation programs also provide VIPs with support in other areas, such as employment training, social skills training, and independent living skills training. The goal of these programs is to help VIPs live as independently and fulfilling lives as possible. For example, a VIP might be taken to a grocery store or a busy street to learn how to navigate these environments safely., this can be reaffirmed by the technical manual of comprehensive rehabilitation services for blind or low-vision people in Latin America [117] and also in the Rehabilitation Manual of the National Center for Rehabilitation for the Disabled of Japan [144]. In this way, there is a specific discipline that is responsible for the study, development, and improvement of O&M for people with visual impairments [152][150].

1.1.3 Orientation and Mobility

Autonomous navigation, which includes determining one's location relative to landmarks(wayfinding) and efficiently and effectively moving from a starting point to a destination (locomotion), is a significant hurdle for individuals with limited vision[205][206]. Orientation and mobility, defined by Blasch et al.[145] as the ability to move independently, safely, and confidently through the environment, is one of the essential elements in the overall rehabilitation process for people with visual impairments. This multifaceted discipline encompasses the fusion of skills, strategies, and adaptive techniques, all meticulously designed to empower individuals in navigating and orienting themselves within their surroundings.

O&M programs encompass instructive modules that are united with orientation techniques. These encompass the proficiency to discern and harness non-visual environmental cues and landmarks. Furthermore, these programs impart a comprehension of both indoor and outdoor spatial configurations, intricacies of directional systems, and the capability to interface with a diverse array of tactile and auditory maps. This multifaceted educational process necessitates the active engagement of cognitive processes, including but not limited to decision-making and problem-solving. Moreover, it imparts a comprehension of spatial dynamics and environmental body concepts, all of which collectively serve as the cornerstone of effective O&M training[205].

Within O&M programs, there is a crucial component dedicated to imparting mobility techniques. These techniques encompass various methods, including but not limited to guided walking with a sighted guide, self-protection strategies, safeguarding one's body from undercarriage obstructions, and the utilization of white canes. These skill sets are pivotal in enhancing the mobility and self-sufficiency of VIP[144].

Thus, O&M training encompasses a comprehensive array of specific instructional modules. These modules go into essential aspects such as safety and self-protection techniques, the art of effectively searching for objects, the cultivation of spatial and environmental awareness, adept white cane utilization in both indoor and outdoor settings, mastering the skills required for efficient route traversal, and much more. These are vital components of the training aimed at empowering VIP to navigate their surroundings confidently and independently[206].

In a recent comprehensive study aimed at understanding the predominant challenges faced by adults with visual impairments concerning the application and accessibility of O&M skills, it was revealed that the overall educational attainment in the domain of O&M remains relatively deficient. As a consequence of this educational gap, adults with visual impairments often find themselves at an increased risk of encountering accidents. These accidents are frequently attributed to several key factors, including insufficient educational provisions, inadequacies in architectural and environmental accommodations, suboptimal transportation arrangements, limited access to assistive technology, the prevailing attitudes of individuals within the community, and the inadequate training of sighted guides. The study brings to light the pressing need for an enhanced focus on education, environmental adaptability, transportation services, assistive technology, and attitudinal transformation to better facilitate the autonomy and safety of people with visual impairments [199].

The field of O&M has been essential in providing VIP with a profound understanding of the significance of adaptability and preparedness when it comes to traversing a wide array of community environments. These O&M training programs are meticulously designed to encompass immersive, experiential learning and real-world exposure, which play an important role in reinforcing and supporting the essential skill sets that are vital for VIP [200].

The advent of the COVID-19 pandemic necessitated PEOPLE to assume more extensive roles beyond their customary responsibilities. Conventional O&M education typically revolves around experiential, hands-on learning and practical exposure, frequently involving the active participation of parents to facilitate skill development. However, the pandemic significantly disrupted these conventional teaching methodologies, sparking contemplation regarding the future direction of O&M services within the field. This includes an exploration of the consequences and potential applications of virtual instruction and online learning in the context of O&M education[200]. Nonetheless, as substantiated by a recent comprehensive systematic review, it becomes evident that virtual rehabilitation programs designed for people with visual impairments represent an understudied domain, demanding a more focused and thorough investigation[201].

Another aspect to focus on within the current challenges in O&M training is the openness to the subjectivity of the training due to its current nature. In rehabilitation practices, the program and assessment of O&M is designed by the trainer and relies on education and formation. This leads to little evidence on which type of O&M training is better for people who have specific characteristics and needs. As the existing literature underscores, there exists a pressing need for consensus regarding the adoption of standardized measurement instruments for evaluating mobility performance, instruments that have been empirically validated as both reliable and sensitive to the diverse spectrum of mobility needs among people with visual impairments[202].

Orientation and mobility training is crucial for people who are visually impaired to help them maintain travel independence. It encompasses the ability to recognize one's position in relation to the environment (orientation) and the ability to move around safely and efficiently (mobility) [232]. This training aims to teach visually impaired people to ambulate and negotiate the environment safely and independently, especially if they undertake independent travel in uncontrolled environments. Orientation and Mobility is a pedagogical practice that blends specific micro-teaching skills to enable students with vision impairment to achieve a functional interpretation of extra-personal and peri-personal space [234].

A study on the travel behavior of blind people before and after receiving orientation and mobility training found that the training had a positive impact on their trip counts, trip distance, and trip duration, indicating an improvement in their ability to travel independently [236]. This highlights the effectiveness of orientation and mobility training in enhancing the travel independence of people with visual impairments [235]. In a dissertation that sought to determine the tools used during assessment and service delivery decisions for school-age children with low vision or blindness, it was found that orientation and mobility specialists play a crucial role in the assessment and service delivery decisions. The study also explored the specialists' perceptions of factors impacting assessment results and service delivery decisions [233]. Orientation and mobility training is a vital component in the lives of people with visual impairments, as it equips them with the skills and knowledge necessary to navigate the world independently and safely. The training not only focuses on the physical aspects of mobility but also encompasses the cognitive and perceptual skills required for effective orientation and mobility.

Orientation and Mobility evolution

O&M training, which focuses on instructing people who are blind or visually impaired with safe and effective travel through their environment, began after World War II when techniques were developed to help blind veterans of the war. Soldiers who had been blinded in battle were sent to recuperate at Valley Forge General Hospital before entering Avon Old Farms Convalescent Hospital, the U.S. Army's former experimental rehabilitation center for blind soldiers in Avon, Connecticut. In the 1960s, universities started training programs for Orientation and Mobility specialists who were to work with adults and school-age children [237]. O&M training is provided to people who are visually impaired to help them maintain travel independence. As explained in the past section, the training aims to teach VIP to ambulate and negotiate the environment safely and independently, especially if they undertake independent travel in uncontrolled environments [238].

The history of OM training for blind people dates back to the post-World War II era when techniques were developed to help blind veterans. Since then, OM training has evolved to become a crucial practice in enabling people with visual impairments to navigate the world safely and independently. The training not only focuses on the physical aspects of mobility but also encompasses the cognitive and perceptual skills required for effective orientation and mobility [237][238].

O&M training for VIP involves a variety of techniques and skills to help them navigate their environment safely and independently. Some of the techniques include the use of canes, such as long canes or white canes, which can help people with visual impairments detect objects and obstacles in their path, as well as maintain their balance. Also, O&M training focuses on environment awareness on helping VIP develop their senses of orientation and mobility by accurately interpreting sensory information available in the environment. On the other hand, mental mapping. This technique involves creating and maintaining a mental map of the environment, using landmarks and environmental clues to supplement any visual clues. The mental map changes as the individual travels, adapting to new surroundings and situations [238]. The trailing technique involves following behind a sighted guide, who can provide verbal cues and guidance to help the people with visual impairments navigate their environment. Squaring off technique involves the people with visual impairments learning to square off with objects or corners, allowing them to navigate through tight spaces or around obstacles. The protective technique involves the sighted guide placing their body between people with visual impairments and potential obstacles, providing a protective barrier and ensuring their safety [143]. The sighted guide technique involves a sighted person assisting people with visual impairments by providing verbal guidance and direction, helping them navigate their environment safely and efficiently. O&M training may also include instruction on navigating specific environments, such as halls, stairs, doorways, curbs, restrooms, restaurants, banks, hotels, pools, parks, and other public spaces[239]. The training may also cover techniques for handling unusual situations, such as navigating through ice, snow, gratings, escalators, revolving doors, elevators, trains, planes, taxis, and other transportation options [239]. These techniques, along with ongoing practice and support, can help VIP develop the skills and confidence needed to navigate their environment safely and independently[238][239].

O&M techniques differ for people with different types of visual impairments. Children and youth with visual impairments may receive a range of special education services, including training in O&M. Because children exhibit a range of visual functioning, O&M instruction can encompass a range of content. Wall-Emerson and Corn (2006) found that experts differed regarding essential O&M skills for students with low vision compared with those for students who are blind [**?**][240]. O&M training is provided to people who are visually impaired to compensate for reduced visual information[240]. The O&M will teach the student to move safely and efficiently through their environment. The O&M may instruct the student in how to get around in special situations (halls, stairs, doorways, curbs, restrooms, restaurants, banks, hotels, pools, parks, etc.) and may also instruct the student in special techniques (trailing, "squaring off," protective technique, sighted guide), and dealing with unusual environmental encounters (ice, snow, gratings, escalators, revolving doors, elevators, trains, plains, taxis, etc.) [241].

O&M training is tailored to the individual's needs and abilities. For example, people with low vision may require different techniques than those who are completely blind. The training may also vary depending on their age, level of visual impairment, and other demographic characteristics [237][242].

It's important to understand that O&M techniques differ for people with different types of visual impairments. The training is tailored to their needs and abilities and may vary depending on the individual's age, level of visual impairment, and other demographic characteristics. O&M instruction can encompass a range of content and may include special techniques and dealing with unusual environmental encounters. However, people with visual impairments face several challenges in learning orientation and mobility techniques [237][242].

Many people with visual impairments may not have access to specialized O&M training due to a lack of resources or trained professionals in their area[143]. Also, VIP may face environmental barriers, such as inaccessible buildings, sidewalks, and transportation systems, which can make it difficult to navigate their environment safely and independently. People with visual impairments may face social stigma and discrimination, which can impact their confidence and willingness to learn new skills. On the other hand, people with visual impairments may have cognitive and perceptual challenges that can impact their ability to learn and apply O&M techniques effectively[**?**]. Some VIP may face financial constraints that limit their access to specialized training, equipment, and technology. Sometimes people with visual impairments may lack support from family, friends, and peers, which can impact their motivation and ability to learn new skills [243]. Addressing these challenges requires a comprehensive and integrated approach that involves specialized training, accessible environments, supportive communities, and innovative technologies.

1.2 Assistive technologies for vision impairment

Assistive technology has significantly improved the quality of life for people with visual impairments by providing tools and devices that help them perform daily tasks. This technology has opened doors and removed countless barriers for VIP, allowing them to be more independent at home, work, and school.

One of the key ways in which assistive technology improves the quality of life for people with visual impairments is by enabling them to perform routine tasks independently. For example, screen reading software and special talking and Braille devices allow people with no vision to use computers, cell phones, and other electronic devices independently[249]. Similarly, people with low vision can use screen magnification software and devices that allow them to see letters, pictures, and other objects without struggling or straining their remaining vision. Assistive technology also enhances access to information and communication for people with visual impairments. For instance, VIP can now read mail, listen to audiobooks, get step-by-step walking directions to unfamiliar places, and record important information with special standalone devices designed for people with no or low vision. This technology has removed many access barriers and fostered greater autonomy for people with visual impairments [249]. This technology has opened doors and removed countless barriers for VIP, allowing them to be more independent at home, work, and school [249].
Some mobile applications have been developed to help blind and visually impaired students develop independent travel skills by providing turn-by-turn directions, real-time street maps, and public transportation schedules [245]. It is also common to see many mobile phones with screen readers as an accessibility tool, which are devices or software that convert text into speech, allowing people with vision impairments to read books, articles, and other written materials. Commercially, there is a wide availability of braille displays available as assistive technology. These are devices that connect to computers or other devices and provide information through a combination of braille characters, allowing people with vision

impairments to access text and graphics. Magnification devices, such as handheld magnifiers or video magnifiers, can help people with vision impairments see objects or text more clearly, as explained before. On the other hand, most of the accessible public places have tactile maps. Tactile maps are raised-relief maps that provide information about the surrounding environment, such as streets, buildings, and public transportation routes, allowing VIP to navigate their community more safely and independently [246]. These assistive technologies is significantly improving the quality of life for VIP by providing them with the tools and resources needed to perform daily tasks, communicate, and navigate their environment more effectively [247]. However, access to these technologies may be limited due to high costs, lack of awareness, trained personnel, policy, and financing. To overcome these barriers, it is essential to promote awareness and accessibility of assistive technologies, as well as provide training and support for people with vision impairments to help them make the most of these tools [248].
Assistive technology has removed many access barriers and fostered greater autonomy for VIP. This technology has removed many barriers to participation and fostered greater inclusion for VIP, enabling them to be more independent at home, work, and school. To ensure that more people benefit from assistive technology, it is essential not only to promote awareness and accessibility of these devices and provide training and support for people with visual impairments, it is also important to create awareness to develop assistive technology, to test assistive technology and to have scientific growth in this research area [250].

Persons with visual or mobility impairments find themselves in a distinct position wherein they need support to execute everyday tasks, including but not limited to tasks like wayfinding, obstacle detection, and safety assurance, regardless of whether they are situated indoors or outdoors. The complexities they encounter become particularly conspicuous when it comes to preparing for journeys or embarking on navigation endeavors in unfamiliar environments. This distinction in experience is pronounced when contrasted with people without disabilities. Beyond typical travel arrangements, they must ensure the accessibility of various components within the travel process [203].

According to the literature, numerous technological solutions have been designed to acquire environmental information and provide assistance to VIP, particularly in enabling autonomous mobility With advances in sensor signal processing and the proliferation of smaller sensor technologies coupled with the advent of Artificial Intelligence(AI), Electronic Travel Aid Systems (ETAS) have emerged as a promising area of focus. These systems encompass a range of applications for visually impaired people, including navigation assistance, mobility support, real-world representation, object and obstacle detection, and other mobility-related functions. In this context, smartphones and wearables equipped with integrated cameras emerge as promising choices to facilitate advanced computer vision solutions for user positioning and environment monitoring. These capabilities can be enhanced through remote resources, including cloud computing systems and urban infrastructure-based remote sensing [204].

The role of assistive technology has grown in significance within the daily lives of VIP. This growing importance can be primarily attributed to recent and groundbreaking advancements in the realm of Artificial Intelligence (AI), renewable energy utilization, and remote delivery mechanisms. These strides have not only increased the accessibility of assistive technology but have also rendered it more cost-effective and, perhaps most efficient. In this context, Mashiata et al. offer a comprehensive insight into the taxonomy and the evolving landscape of assistive devices and technology specifically tailored to cater to the unique needs of VIP (Figure 1.4).[202].

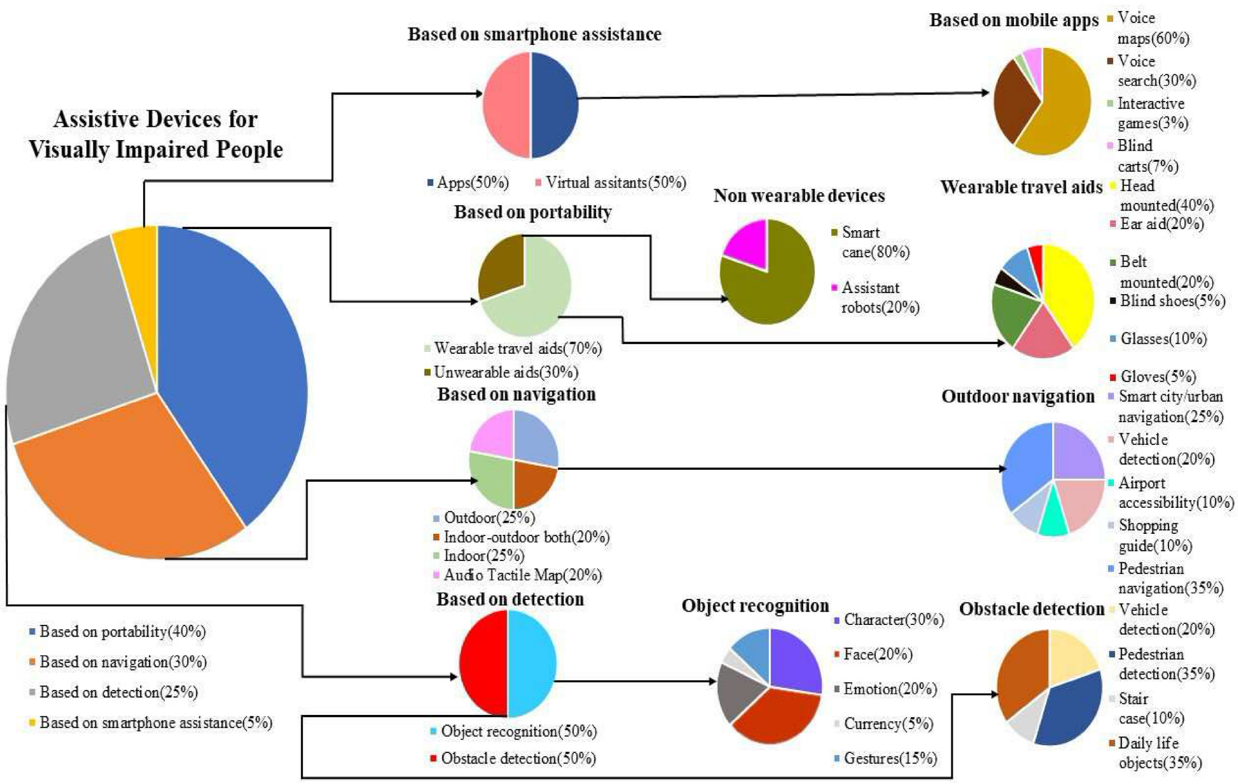

Figure 1.4: Record of existing papers for visually impaired people Source: [202]

This comprehensive review provides a detailed categorization of the progress in assistive technology designed for VIP, as illustrated in Figure 1.4. The predominant focus in the existing body of literature centers on solutions tailored for outdoor navigation, wearable travel aids, and the crucial domain of object recognition and detection. These areas represent the primary facets of research and development in the field of assistive technology for the visually impaired. Electronic navigation aids tailored for VIP have been subject to considerable development efforts. However, a noteworthy portion of these aids is reliant on intricate architectural designs, which in turn introduce certain challenges when it comes to effectively perceiving and understanding the surrounding environment[202].

Within the domain of technological advancement for rehabilitation, the available literature highlights a notable lack of developments. One O& M rehabilitation system was found as identified in the relevant research[134]. This system is intricately designed with the specific objective of enhancing and refining auditory orientation training, addressing an area within rehabilitation that requires further attention and innovation.

Furthermore, assistive technology has facilitated the inclusion of VIP in various settings, such as work and school. By providing tools and devices that enable them to perform tasks independently, this technology has removed many barriers to participation and fostered greater inclusion VIP.[250] For example, individuals can now write documents, browse the internet, and send and receive emails independently, thanks to screen reading software and special talking and Braille devices [250]. Despite the numerous benefits of assistive technology, many people with visual impairments do not use these devices. According to recent data, only 12.4 percent of adults 18 years and over with visual impairment use assistive and adaptive devices in 2017. To increase the use of assistive technology, it is essential to recommend these devices during vision rehab and include visual aids in smartphones or screen readers. Additionally, promoting awareness and accessibility of assistive technologies, as well as providing training and support for VIP, can help more people benefit from these tools [251]

Assistive technology Customization

Customizing assistive technology to meet the needs of VIP is crucial for ensuring that they can effectively perform daily tasks, communicate, and navigate their environment. There are several ways in which assistive technology can be tailored to the specific needs of VIP:

- Personalized Training and Support: Providing personalized training and support for VIP can help them learn how to use assistive technology effectively and integrate it into their daily lives. This training should be tailored to the individual's specific needs, goals, and abilities, and may include instruction on how to use specific devices and software, as well as strategies for overcoming barriers and challenges [245].
- Adapting Devices and Software: Adapting devices and software to meet the specific needs of devoid can help them access information, communicate, and perform daily tasks more effectively. For example, screen reading software and special talking and Braille devices can be customized to provide information in a format that is accessible to people with no or low vision [**?**].
- Incorporating Feedback and Input: Incorporating feedback and input from devoid into the design and development of assistive technology can help ensure that it meets their specific needs and preferences. This may involve conducting user testing and research to identify barriers and challenges, as well as gathering input on how to improve the accessibility and usability of devices and software [**?**].
- Promoting Awareness and Accessibility: Promoting awareness and accessibility of assistive technology can help ensure that VIP are aware of the tools and resources available to them, and can access them easily. This may involve providing information and training on how to use specific devices and software, as well as advocating for the development of new tools and resources that meet the specific needs of VIP [**?**].
- Providing Ongoing Support and Resources: Providing ongoing support and resources for VIP can help them learn how to use assistive technology effectively and integrate it into their daily lives. This may involve providing access to training, support groups, and other resources that can help them learn how to use specific devices and software, as well as strategies for overcoming barriers and challenges[**?**].

Customizing assistive technology to meet the needs of people with visual impairments is crucial for ensuring that they can effectively perform daily tasks, communicate, and navigate their environment. This may involve providing personalized training and support, adapting devices and software, incorporating feedback and input, promoting awareness and accessibility, and providing ongoing support and resources. By tailoring assistive technology to the specific needs of VIP, it is possible to ensure that they have access to the tools and resources they need to live more independently and effectively.

Some common features for the customizing of assistive technology for VIP may include:

- Screen Reading Software: Screen reading software converts text on a computer or mobile device screen into speech or braille, allowing VIP to access and interact with digital content [254].
- Magnification Software and Devices: Magnification software and devices enlarge text and images on computer screens, tablets, and smartphones, allowing people with low vision to see and interact with digital content more easily [254].
- Braille Displays and Notetakers: Braille displays and notetakers provide tactile access to digital content, allowing VIP to read and write in braille [254].
- Voice Recognition Software: Voice recognition software allows VIP to control and interact with digital devices using their voice, enabling hands-free operation [253].
- Navigation and Wayfinding Apps: Navigation and wayfinding apps provide turn-by-turn directions, real-time street maps, and public transportation schedules, allowing VIP to navigate their environment more independently [253].
- Descriptive Video Players: Descriptive video players provide audio descriptions of visual content, such as television shows and movies, allowing VIP to access and enjoy visual media more fully [254].
- Tactile Graphics and Maps: Tactile graphics and maps provide tactile access to visual content, such as diagrams, charts, and maps, allowing VIP to access and interact with visual information more effectively [248].
- Electronic Magnifiers: Electronic magnifiers provide high-magnification, high-contrast views of printed materials, such as books, documents, and labels, allowing people with low vision to read and interact with printed content more easily [248].

These features of assistive technology are designed to provide people with visual impairments with the tools and resources they need to access and interact with digital and visual content more effectively, enabling greater independence and autonomy in their daily lives.

1.2.1 Gait in Orientation and Mobility

Gait, defined as the pattern of walking, constitutes an integral and indispensable component of O&M training. This facet is fundamental for VIP, enabling them to navigate through their surroundings with an emphasis on safety and self-sufficiency. The mastery of gait is a fundamental prerequisite for achieving autonomous travel and effective navigation in diverse environments.

Gait analysis is a critical component of biomechanics that involves the study of human motion, particularly walking and running. It is a multidisciplinary field that combines principles from anatomy, physiology, kinesiology, and engineering to understand the complexities of human movement. Gait analysis has numerous applications in sports science, rehabilitation, orthopedics, and ergonomics. The study of gait involves the measurement and analysis of various parameters, including kinematics, kinetics, and muscle activity, to gain insights into the underlying mechanisms of human locomotion [255].

- Kinematics and Kinetics of Gait Gait analysis encompasses the study of both kinematics and kinetics of human motion. Kinematics refers to the description of motion, including joint angles, segmental movements, and the trajectory of body parts during gait. Kinetics, on the other hand, involves the forces and torques that cause or result from motion. Both kinematic and kinetic data are essential for a comprehensive understanding of gait patterns and abnormalities [256].
- Biomechanical Perspectives From a biomechanical perspective, gait analysis involves the application of mechanical principles to the study of human motion. This includes the analysis of forces, moments, and energy expenditure during walking and running. Biomechanical studies have contributed significantly to the understanding of gait abnormalities and the development of interventions to improve gait performance [256].
- Clinical Applications Gait analysis has important clinical applications in the fields of orthopedics, rehabilitation, and sports medicine. It is used to assess gait abnormalities, diagnose musculoskeletal disorders, and monitor the progress of rehabilitation programs. Gait analysis can provide valuable information for treatment planning and outcome evaluation in clinical settings [256].

Gait analysis is a multidisciplinary field that plays a crucial role in understanding human locomotion. By integrating knowledge from anatomy, physiology, kinesiology, and engineering, researchers and practitioners can gain valuable insights into the complexities of gait. Advanced techniques such as causal decomposition and musculoskeletal modeling have the potential to further advance our understanding of gait and its clinical applications. There are various methods used to study gait, which can be broadly classified into qualitative and quantitative approaches. Observational Gait Analysis (OGA): This method involves clinician's observation, video slow-motion replay, and/or freeze-frame techniques to record and analyze a patient's gait. It relies on visual cues to compare asymmetries and find abnormalities [257]. Kinematic Analysis: This method involves the measurement of lower and upper body joint motion during gait, including joint angles, range of motion, and spatio-temporal parameters [258]. Kinetic Analysis: This method focuses on the forces and moments involved in gait, providing insights into the energy expenditure and muscle activity during walking and running [259]. Instrumented Gait Analysis: This approach uses specialized equipment such as motion capture systems, force plates, and wearable sensors to quantify various parameters of the gait cycle, including joint angles, ground reaction forces, and temporal-spatial parameters [260].These methods offer different levels of accuracy and precision in gait analysis, with quantitative approaches providing more objective and detailed data compared to qualitative methods.

The choice of method depends on the specific research or clinical objectives, as well as the available resources and expertise. The study of gait involves a spectrum of methods, ranging from simple observational techniques to advanced instrumented analysis. Each method has its advantages and limitations, and the selection of the appropriate approach depends on the specific requirements of the study or clinical application[261].

Additionally, the analysis of gait patterns holds significant importance across a spectrum of rehabilitation applications. Conventional optical motion analysis systems, while effective, exhibit certain inherent limitations, encompassing factors such as substantial cost, fragility, limited portability, and demanding resource prerequisites[173]. Inertial Measurement Units (IMUs) have emerged as a new method for measuring gait parameters. IMUs are small, wearable devices that can measure a person's movement and orientation. By combining IMUs with magnetometers, which measure magnetic fields, it is possible to obtain accurate measurements of gait and posture.

Among the populations that could benefit from gait measurement and biomechanical analysis (i.e., the study of gait and posture), VIP are particularly noteworthy.[146].

Employing inertial sensors integrated into smartphones, especially when leveraging deep learning techniques for gait analysis, necessitates a substantial volume of training data. Additionally, it may not exhibit optimal adaptability to the distinctive gait patterns and characteristics exhibited by VIP [130].

1.2.2 Wearables for gait analysis

Wearable systems offer several advantages for gait analysis, making them increasingly popular in research and clinical settings. These sensors are widely used because of their portability and long-term monitoring, wearable sensors allow for gait analysis in real-world environments, enabling long-term monitoring of gait patterns during daily activities [262]. This portability and continuous monitoring provide a more comprehensive understanding of an individual's gait patterns outside the laboratory setting. Wearable systems facilitate gait assessment over ample walking distances and in various environmental conditions, including different walking surfaces and footwear, which better replicates real-world scenarios compared to laboratory-based systems [263]. Wearable technologies are often more cost-effective and accessible compared to traditional laboratory-based motion tracking systems, making them suitable for widespread use in both research and clinical practice [264]. Wearable devices can capture more spontaneous gait information, allowing for the assessment of gait patterns during activities such as sports and recreational activities [265].

Wearable systems offer several advantages for gait analysis, including portability, naturalistic gait assessment, cost-effectiveness, and the ability to capture spontaneous data. These advantages make wearable sensors a valuable tool for both research and clinical applications in the study of human gait[265]. Wearable sensors offer a range of options for gait analysis, including accelerometers, gyroscopes, magnetometers, force sensors, IMUs, pressure sensors, and EMG sensors. These sensors can be used alone or in combination to capture various aspects of gait, providing valuable insights into human locomotion.

There are various types of wearable sensors used for gait analysis, each with its unique capabilities and applications. Wearable sensors have revolutionized the field of gait analysis by enabling the collection of data in real-world environments, providing valuable insights into human locomotion. The following is a detailed exploration of the different types of wearable sensors used for gait analysis:

- Accelerometers: Accelerometers are widely used in gait analysis to measure the acceleration of body segments during movement. They can provide information on step count, gait speed, and gait symmetry, making them valuable for assessing gait patterns in both research and clinical settings [266].
- Gyroscopes: Gyroscopes measure the rate of rotation and angular velocity of body segments during gait. They are particularly useful for assessing the rotational movements of the body, such as the rotation of the trunk and pelvis during walking and running [260].
- Magnetometers: Magnetometers measure the Earth's magnetic field and can be used to determine the orientation of the body during gait. They are often used in combination with accelerometers and gyroscopes to provide a more comprehensive assessment of gait patterns [260].
- Force Sensors: Force sensors measure the forces acting on the body during gait, such as ground reaction forces and joint forces. They are valuable for assessing the distribution of forces during walking and running, as well as for monitoring changes in gait patterns over time [266].
- Inertial Measurement Units (IMUs): IMUs combine accelerometers, gyroscopes, and magnetometers to provide a comprehensive assessment of body motion during gait. They are often used in wearable gait analysis systems to capture a wide range of gait parameters, including kinematics, kinetics, and spatio-temporal parameters [267].
- Pressure Sensors: Pressure sensors are used to measure the distribution of pressure under the foot during gait. They can provide valuable information on gait abnormalities, such as foot pressure asymmetries and changes in pressure distribution over time [268].
- Electromyography (EMG) Sensors: EMG sensors measure the electrical activity of muscles during gait, providing information on muscle activation patterns and timing. They are valuable for assessing muscle function and coordination during walking and running [266].

Wearable sensors allow for gait analysis in real-world environments, enabling long-term monitoring of gait patterns during daily activities [130]

Devices	Gait Measures	Pros	Cons
Smartphone	● GPS ● Walking days, distance, frequency, and rotation, etc. ● Spatiotemporal measures	● Simple data acquisition on spatiotemporal gait characteristics ● Widely used devices ● With user interface ● Telemedicine services	● Lower precision on data collection (i.e., not fit well in the mechanically turbulent phases) ● Not enough types of data (i.e., not including kinetics, range of motion, etc.)
Wearable Sensors	● Orientation, horizontal, position ● Biomechanical measures (i.e., mass, barycenter, rotation inertia, and stability etc.) ● Gait kinematics (i.e., range of motion, spatiotemporal measures, etc.) ● Gait kinetics (i.e., plantar pressure, GRF, joint torque, etc.) ● EMG	● Tiny size ● Low cost ● Low power consumption ● Easy-to-perform ● High sensitivity on data acquisition	● Foreign-body sensation ● Lower accurate and precise measurements than gold-standard system ● Difficult in complex signal detection
Sensing Fabrics	● Pressure ● Bioimpedance ● Physical quantities (i.e., conductivity, temperature, and elongation etc.)	● Soft, light, waterproof, stretchable ● High pressure sensitivity ● Long service ● Stable data acquisition (both static and dynamic measurements)	● Not breathability ● High-cost ● No mature product

Figure 1.5: Pros and cons of different types of wearable devices. Source: Liu et al. [268]

Moreover, recent comprehensive evaluations have underscored the dearth of IMU-based systems carefully designed to meet the specific needs to the specific needs of VIP. Furthermore, a lack of available literature addressing biomechanical analysis rooted in IMU technology for this particular demographic has been emphasized. While portable IMU sensors have garnered significant recognition and usage within clinical research to investigate various aspects of gait parameters in conditions such as stroke, Parkinson's disease, and multiple sclerosis, there is presently a conspicuous gap in the scientific literature concerning the biomechanical intricacies about VIP [174].

Currently, available non-portable systems for analyzing the walking patterns of VIP come with certain limitations, and there is an observable absence of portable systems that are tailored to the specific requirements of these population.

Spatio-temporal gait parameters are essential for understanding and assessing human walking behavior. These parameters can provide insights into the differences between healthy and pathological gait patterns, as well as the impact of various factors on gait performance. Various methods, such as foot-worn inertial sensors, interactive models, normative databases, and wearable sensors, have been used to measure these parameters in healthy and pathological gait patterns. Further research is needed to explore the impact of different factors on gait performance and to develop more accurate and reliable methods for assessing spatio-temporal gait parameters [269][270].

The advantages of using inertial sensors to measure spatio-temporal gait parameters are supported by recent scientific research. A study published in 2021 found that spatio-temporal gait parameters measured with foot-worn inertial sensors were reliable in healthy adults, both in single- and dual-task conditions. This reliability makes inertial sensors a valuable tool for assessing gait in various contexts [271]. A study published in 2023 demonstrated that inertial sensor-based systems are a valid alternative to laboratory gait analysis systems for analyzing spatio-temporal gait parameters in people with multiple sclerosis. The study concluded that these systems are user-friendly and can quickly collect a large amount of data concerning a patient's gait [272]. The study published in 2020 aimed to verify the accuracy of an IMU system for measuring spatio-temporal and kinematic parameters of gait. The study compared the IMU system with a reference system based on optical motion capture (OMC) for gait analysis. The results showed that the IMU system was effective for measuring spatio-temporal parameters, such as gait speed, stride length, and gait cycle, and that the measurements obtained were in high agreement with those from the OMC system. The study concluded that the IMU system is a reliable and valid tool for gait analysis, which can be used in clinical and research settings [269]. This research provides valuable evidence supporting the use of IMU systems for measuring spatio-temporal gait parameters, which has significant implications for gait analysis in both research and clinical settings [273].

Furthermore, the majority of analyses related to spatial-temporal gait parameters in VIP have traditionally relied on motion tracking systems. Additionally, assessments of independent mobility and O&M rehabilitation have predominantly depended on visual approximations rather than precise quantitative measurements[177].

1.3 Research Objectives and Hypothesis

This thesis endeavors to facilitate the basis for the development of inertial sensor-based assistance tools capable of providing data relevant to the context of orientation and mobility rehabilitation training.

Building on the problem statement and relevant background detailed in Sections 1.1 and 1.2, the main contributions of this thesis include:

1. IMU-based systems for Visually Impaired People (Chapter 3) 2. Measurement of Long Cane techniques (Chapter 4) 3. Gait and Posture spatiotemporal parameters (Chapter 5) 4. Interfaces for Visually Impaired people using computer vision (Chapter 6) 5.Deep Learning models to estimate gait parameters in Visually Impaired People

1.3.1 General Objective

Develop and evaluate novel assistive technologies for visually impaired people using inertial measurement unit sensors and computer vision-based models to address the challenges and limitations of existing technologies for rehabilitation to improve the basis of mobility, independence, and quality of life of visually impaired.

1.3.2 Specific Objectives

- Identify and address the challenges and limitations of IMU sensors in assistive technologies for visually impaired people.
- Evaluate the effectiveness of the proposed low-cost motion measurement system in supporting VIP during rehabilitation exercises compared to existing solutions.

- Develop and evaluate the reliability and accuracy of wearable sensors for measuring spatio-temporal parameters of gait and posture in visually impaired people.
- Develop and evaluate a user-friendly computer vision-based model with object detection for visually impaired needs in interaction with machines.
- Evaluate LSTM-based deep learning models to estimate gait parameters in visually impaired people and compare it with traditional estimation biomechanical models.

1.3.3 Hypothesis

The integration of inertial wearable sensors can significantly improve the accuracy and effectiveness of mobility assessment and support for VIP.

1.4 Thesis organization

In this thesis, chapters 3–6 each contain a paper that has been peer-reviewed and accepted for publication in a journal(3-5) and conference (6). The papers were left unmodified from their published forms, except for formatting changes. The thesis is structured as follows.

Chapter 1: Introduction

Chapter 2: Methodology

Chapter 3: Inertial Measurement Unit Sensors in Assistive Technologies for Visually Impaired People, a Review

Reyes Leiva, Karla Miriam, Milagros Jaén-Vargas, Benito Codina, and José Javier Serrano Olmedo. 2021. Sensors 21, no. 14: 4767. https://doi.org/10.3390/s21144767 (Q1)

Chapter 4: A Proposal of a Motion Measurement System to Support Visually Impaired People in Rehabilitation Using Low-Cost Inertial Sensors

Reyes Leiva, Karla Miriam, Milagros Jaén-Vargas, Miguel Ángel Cuba, Sergio Sánchez Lara, and José Javier Serrano Olmedo. 2021. Entropy 23, no. 7: 848. https://doi.org/10.3390/e23070848 (Q2)

Chapter 5: Estimation of Spatio-Temporal Parameters of Gait and Posture of Visually Impaired People Using Wearable Sensors

Reyes Leiva, Karla Miriam, Miguel Ángel Cuba Gato, and José Javier Serrano Olmedo. 2023. Sensors 23, no. 12: 5564. https://doi.org/10.3390/s23125564 (Q1)

Chapter 6: Computer Vision-Based Assistance System for Visually Impaired Individuals in Vending Machine Interactions

Reyes Leiva, Karla Miriam, Zeid Daou, Roy Abi, Serrano Olmedo, José Javier. 2023. IEEE CONCAPAN XLI Tegucigalpa, November 2023.

Chapter 7: Evaluation of LSTM based models for the estimation of gait parameters in visually impaired people

Reyes Leiva, Karla Miriam., Orellana, Jennifer., Elyasi, Fatemeh., Manduchi, Roberto., Serrano Olmedo, Jose Javier.

Submitted to the 2024 International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)

Chapter 8: General Discussion

Chapter 9: Additional Research and Data

Chapter 10: Conclusions

Conference publications not included in this thesis

*· Development of a motion measurement system of a long cane for Visually Impaired People in rehabilitation (Conference paper)

XXXVIII Congreso Anual de la Sociedad Española de Ingeniería Biomédica, November 2020. Karla Miriam Reyes Leiva, Sergio Sanchez, Milagros Jaén Vargas, José Javier Serrano Olmedo

*· A simplified methodology to measure gait spatio-temporal parameters using low-cost inertial sensors (Conference paper)

XXXIX Congreso Anual de la Sociedad Española de Ingeniería Biomédica, Madrid, November 2021. Karla Miriam Reyes Leiva, Miguel Cuba, José Javier Serrano Olmedo

*· Accessibility of interfaces for Orientation and Mobility rehabilitation of visually impaired people. (Conference poster)

RehabWeek, Rotterdam, July, 2022. Karla Miriam Reyes Leiva, Milagros Jaén-Vargas, Thomas Busato, Malaury Bauthier, Ángela Suarez, José Javier Serrano Olmedo

*· Algoritmos de aprendizaje profundo para la estimación del tamaño de zancada utilizando sensores inerciales. (Conference poster)

5th National Congress on Science, Technology and Innovation. Tegucigalpa, August, 2023 Karla Miriam Reyes Leiva, Reyna Elizabeth Valle Ordoñez, Manuel Gamero

Chapter 2

Methodology

This thesis is a compendium of articles, each of which presents the results of a research study, this article follows a research topic and problem. A detailed description of the research methodology used in each of the chapters is described as follows:

Chapter 3: This chapter presents a systematic review of the use of inertial measurement unit (IMU) sensors in assistive technologies for visually impaired people. A literature search was conducted following the PRISMA criteria. The IEEE Xplore, Web of Science, and PubMed databases were used for reviewing articles published until December of 2020. The following terms were used in the search:

IMU*, accelerometer, gyroscope, magnetometer, inertial measurement, visually impaired, blind, visual impairment.

Articles were included in the review if they met the following criteria: (1) proposed systems including IMU sensor technology (2) implementation of IoT systems (3) rehabilitation or physical monitoring and (4) experimental results of their developments, including the participation of volunteers.

A total of 40 articles met the eligibility criteria. The articles were divided into four categories according to the type of IMU sensor used

Chapter 4: This study presents a developed tool to evaluate rehabilitation parameters during the experimental procedure.

In this study, a quantitative method and experimental design was developed to test the effectiveness of the developed tool to evaluate rehabilitation parameters.

The tool was developed using two 9DOF BNO055 IMU Bosch sensors, an Arduino MKR1010 microprocessor, and an SD card module. The IMU sensors were placed on the outer side of the leg of each participant and on the higher part of a 117 cm long cane. Serial communication was done via I^2C protocol at a sample rate of 0.01 s. A low pass filtering was performed with a cutoff frequency of 20 Hz to remove noise components from the signal.

To calculate step length, an algorithm was developed using the Euler roll angle θ_{leg} To obtain the sweeping metrics, the Euler roll ϕ_{cane}, pitch θ_{cane} , and yaw γ_{cane} angles were used to provide the grip rotation, the safety zone metrics, and sweeping characteristics consecutively.

Ten blindfolded volunteers participated in the experimental procedure. First, the volunteers were instructed and trained for each travel technique while sighted. A floor carrel was marked for the sweep training with an amplitude of around 1 m. The volunteers were asked to train each technique walking 20 steps three times. After that, they were blindfolded and asked to perform the travel techniques when displacing around 20 steps in the indicated direction. Each acquisition was repeated blindfolded three times, obtaining nine comparative metrics for each participant. The total time was measured using a chronometer to serve as reference values to evaluate the accuracy of the measured gait parameters. Descriptive statistics and inferential statistics were performed.

Chapter 5:

This study employed a mixed-methods approach to evaluate the accuracy of two methods for estimating step length, distance, and velocity in visually impaired people using IMU sensors. Nine visually impaired volunteers were recruited and tested in five different walking conditions with varying velocities.

The first method, the two-sensor (TWS) configuration, used two IMUs placed on the thigh and shank of one leg to measure orientation angles. The second method, the thigh sensor (THS) configuration, used a single IMU placed on the thigh to measure orientation angles.

In this study, a combination of the collection of quantitative measures (step length, distance velocity, and standard deviation) and qualitative inputs (observation and evaluation of participants' postural changes) was done. A single-step counting (SC) algorithm was used for both methods. The algorithm identified a new step when the leg crossed the vertical position and detected the local maximum and local minimum in each inflection point of the rotation angle patterns. A straightforward activity recognition algorithm, based on angular velocity, was also developed to determine whether the user was moving or not. Step length (SL) was calculated using the cosine law, considering the lengths of the hip-heel segments for each leg and the rotation angle between the heel strike and heel off. Distance (D) was calculated as the summation of the measured SL for every identified step. Gait velocity (GV) was determined by dividing D by the total walking time. Postural stability was assessed using a single IMU placed on the participants' backs to measure orientation. The standard deviation of the roll and pitch angles was calculated to assess postural sway. A posture evaluation based on the video recordings was also conducted to confirm that the standard deviations obtained from the orientation angles were capable of detecting significant postural changes that affected heading, inclinations, and balance during walking tasks.

A Single-group design was used as the experimental design, with a variation of conditions for data collection in 9 visually impaired volunteers. Then mean absolute error was calculated for the study variables.

Chapter 6:

For this study, a methodology was settled for the development of a dataset and the training of a deep learning model to identify and classify vending machines and their components.

Six different types of vending machines were identified at two universities. These types varied based on the products they dispensed and their appearance.Due to constraints on access and time, three main types of vending machines were selected for creating the dataset: Cold Beverages (B), Snacks and Food (D), and Drink and Snacks V.M. (F). Data Set Creation: Points in the city and on campus were identified using Open Street Maps, and images of the vending machines were collected. Around 105 images were obtained from Google search. These images were annotated initially using CVAT and then managed using the Roboflow platform. The original dataset contained 32 classes covering vending machine types, parts, and products.

The YOLOv5 Ultralytics repository was used for training the models in Google Collaboratory. Initially, models were trained with the original dataset, and then the dataset was preprocessed and augmented to improve performance. Various training parameters such as input image size, batch size, and training epochs were adjusted. Model Evaluation: The trained models were evaluated using a testing dataset. Results showed high accuracy in identifying vending machine types and parts, as well as most products. However, there were some errors and lower accuracy in recognizing tags and certain products.

Chapter 7:

In this final study, the aim was to evaluate LSTM-based algorithms for estimating gait parameters in VIP. The methodology adapts the experimental setup from a previous study, involving walking tasks in various conditions. Data processing involves verifying and validating collected data using video recordings. Two main LSTM-based models, 4FCN+LSTM and CNN+LSTM, are tested, employing preprocessing, training, and validation steps. Additionally, an alternative Sequence-To-One LSTM+FCN model is explored for summarizing temporal information into a single prediction. The models utilize various layers and activation functions, with dropout to prevent overfitting and RMSprop optimizer for efficient weight updates. Data augmentation and preprocessing techniques are employed to enhance model performance.

Chapter 3

Inertial Measurement Unit Sensors in Assistive Technologies for Visually Impaired People, a Review

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Abstract

A diverse array of assistive technologies have been developed to help Visually Impaired People (VIP) face many basic daily autonomy challenges. Inertial measurement unit sensors, on the other hand, have been used for navigation, guidance, and localization but especially for full body motion tracking due to their low cost and miniaturization, which have allowed the estimation of kinematic parameters and biomechanical analysis for different field of applications. The aim of this work was to present a comprehensive approach of assistive technologies for VIP that include inertial sensors as input, producing results on the comprehension of technical characteristics of the inertial sensors, the methodologies applied, and their specific role in each developed system. The results show that there are just a few inertial sensor-based systems.

However, these sensors provide essential information when combined with optical sensors and radio signals for navigation and special application fields. The discussion includes new avenues of research, missing elements, and usability analysis, since a limitation evidenced in the selected articles is the lack of user-centered designs. Finally, regarding application fields, it has been highlighted that a gap exists in the literature regarding aids for rehabilitation and biomechanical analysis of VIP. Most of the findings are focused on navigation and obstacle detection, and this should be considered for future applications.

Keywords: accelerometer; assistive technologies; gyroscope; IMUs; visually impaired; usability

3.1 Introduction

According to the World Health Organization, about 28% of the global population (2.2 billion) is visually impaired or blind [1]. Vision impairments have different limitations, including distance and near-vision impairment. As technology advances, there is a need to develop high-quality assistive systems for the inclusion of visually impaired people (VIP) into a technological world to improve their Quality of Life (QoL) and to facilitate daily challenges such as finding and keeping a job, mobility, using public transport, and doing physical activity (PA) [2] [3] [4] [5] [6]. With the ongoing progress in computer science, such as deep learning, and in hardware development, such as sensor miniaturization, researchers have developed human activity recognition (HAR) algorithms that enable automatic feature extractions [7] [8] [9], for instance, by using inertial sensor's acquisitions as input data [10] [11] [12] [13] [14] .

In addition, there are great advances in miniaturized sensors capable of providing parameters of moving objects, such as position and velocity [15][16][17]. The fusion of the advances in both sensors and artificial intelligence has led to many projects that seek to support VIP in navigation [18][19][20][21][22][23][24][25][26][27], traveling [28][29][30][31], representation of the real world [32][33][34][35], obstacle detection on wayfinding [29][36][37][38], assistant robots [39][**?**], and other applications for general mobility, for monitoring and improving PA, and for sports participation of the VIP [**?**][42][43][44]. The application spectrum is extensive and may include even sensor fusion for monitoring the vital signs of guide dogs in training [45]. However, a large quantity of these systems are designed to provide VIP with information obtained from their surroundings. Electronic Travel Aid Systems (ETAS) [**?**] are one of the most studied assistive technologies and, according to the recent state of the art, wearable assistive devices for the visually impaired can be divided into two categories: Video camera-based ETAS and Sensorial network ETAS. Sensorial network ETAS are based primarily on GPS, BLE beacons, RFID, Ultrasound sensors, and Infrared sensors [3][46].

An important factor constraining the development of these assistive technologies is that there are limitations regarding the accuracy of these systems. Another important factor is poor acceptance by the blind community, which is a factor related to the limitation of the visual rehabilitation programs in which these systems should be included [47]. Technologies based on inertial measurement unit sensors (IMU) are used in a large and ever-growing number of applications such as intelligence guidance, mineral exploration, self-driving robots [15], full-body motion tracking [48][49][50][51][52][53], and navigation as well [54][55]. IMUs are widely used because they provide positioning information based on the dead-reckoning method, which determines the current position based on estimates of velocity and heading, departing from a known previous position. This type of navigation and tracking information is useful in areas where infrastructure-less positioning systems are required [56], including VIP applications.

There is a large amount of literature on the use of inertial sensors to estimate position and orientation. However, as mentioned before, sensor acquisition in ETAS and other VIP systems developed for navigation and assistance are not primarily IMU-based technologies, although their sensing includes IMUs data. This is due to integration drift, which is a known disadvantage of IMUs that can generate position errors in the dead-reckoning method. To face the drift error, many authors suggest incorporating inertial measurement as part of the acquired sensing and fusing the values with the sensing of optic sensors and global positioning systems (GPS) also to include the drift reduction algorithms, which greatly contribute to a more accurate positioning within IMU data [56][57][58].

As mentioned before, there is a wide range of applications for IMUs. The aims of this systematic review are as follows: (1) to provide an overview of current state of the art research and development on technology that implements IMU sensors in support of VIP; (2) to provide an understanding of how IMU sensors work and how they are used in current developments; (3) to review challenges currently faced in research focused on assisting VIP; (4) to explore application fields, besides those for navigation, in which these types of sensors can be used to support VIP. To enhance reproducibility, the details of the procedure are provided; this is a thematic review in which we pre-selected for content as described below and in which additional relevant findings are discussed.

3.2 Materials and Methods

3.2.1 Literature Search Method

Literature searches were performed in the IEEE Xplore (IE), Web of Science (WoS), and PubMed databases. Considering rapid advances in technology, we focused on articles published in the last 5 years (until December 2020) to give an overview of the most recent developments. Searches were performed in IE, WoS, and PubMed on 15 December 2020. Only articles written in English were considered. Our screening was filtered in two stages: a general search and a refinement in the three databases. Terms used in the general search were (IMU* OR accelerometer OR gyroscope OR magnetometer OR inertial measurement). For the refinement, the terms were (visually impaired OR blind OR visual impairment).

3.2.2 Eligibility Criteria

The following criteria were used to select the articles included in this review: (1) articles with proposed systems including IMU sensor technology with at least one kind of measurement (accelerometer, gyroscope), (2) in the implementation of IoT systems on the developments and (3) rehabilitation or physical monitoring of daily life activities and (4) in publications within experimental results of their developments, including the participation of VIP or blindfolded (BF) volunteers.

3.2.3 Inclusion Criteria

The initial search resulted in 637 articles (IEEE = 85, WoS = 324, PubMed = 264). To be included in this review, the aim of an article was required to be a development to aid VIP exclusively; articles regarding navigation, human motion, or PA monitoring not developed for VIP were excluded. After applying the selection criteria and removing duplicates, 40 articles remained to be reviewed (Figure 1).

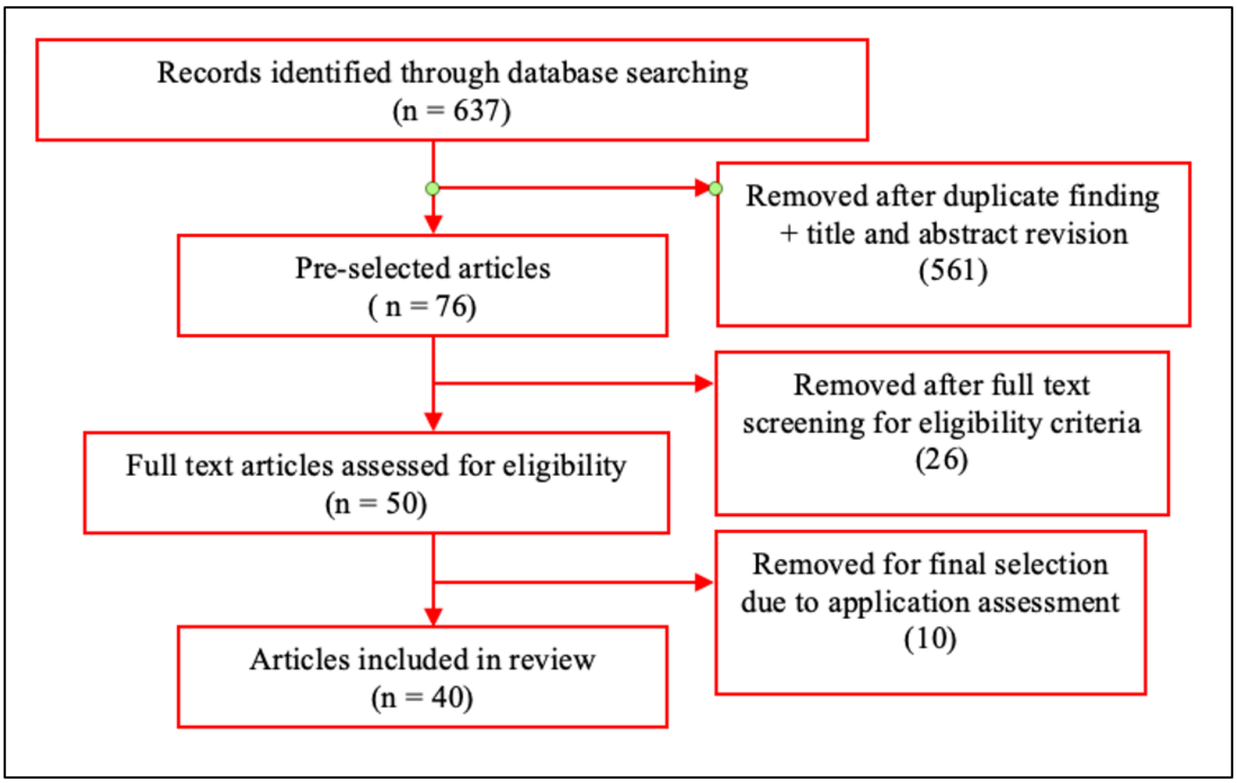

Figure 3.1: Deep analysis article selection process after database searching.

3.3 Results

The articles were summarized and divided into four categories according to the inertial sensor used, "sensor input". The first section discusses nine articles reporting to use accelerometer input, the second section considers four articles that used gyroscope input, the third and four sections discuss 13 articles using both accelerometer and gyroscope input and 14 articles reported that used accelerometer, gyroscope, and magnetometer input.
Then, the usability, the application trends, and the artificial intelligence incorporation in the

reviewed articles are discussed. Note that in the extension of this section, the role of the inertial measurement unit in each development is highlighted; however, most of the selected articles integrate sensor fusion in which other types of sensors (non-inertial) are used.

3.3.1 Accelerometer

As shown in Table 1, 23% of the reviewed articles reported the use of an accelerometer. An accelerometer measures the external specific force acting on the sensor, which consists of both the sensor's acceleration and the acceleration due to the earth's gravity. The accelerometer input served several purposes, including position estimation, monitoring of physical movement, and vibration detection. The most frequently used accelerometers included ActiGraph from Actigraph Corp, ADXL from Analog Devices, and KXR from Kionincs.

Table 3.1: Table 1. Summary of reviewed articles in the accelerometer section.

Role	IMU	Sensor Fusion	Ref.
Identify human movement	ADXL345	RGB Camera, Ultrasonic Sensor	[59]
Measures physical activity	ActiGraph GT3x	N/A	[60]
Measures physical activity	ActiGraph wGT3X-BT	N/A	[61]
Measures physical activity	ActiGraph wGT3X-BT	N/A	[62]
Measures physical activity	ActiGraph wGT3x+	N/A	[63]
Sense the foot movements	KXR94-2050	N/A	[64]
Measures physical activity	ActiGraph GT3x	N/A	[65]
Measures physical activity	ActiGraph GT3x	N/A	[66]
Monitoring of human activities	Not specified	N/A	[67]

The Actigraph Corp wearable accelerometers were used in many clinical trials found in the systematic review. The accelerometers were used to measure PA within the VI community, with a major experimental focus on kids and older adults [60][61][62]. Since the blind spend more time in sedentary activities, trials attempted to determine relationships between falls and levels of PA [63]. These wearable sensors present output data of the three-accelerometer axis independently and provide activity counts as a composite vector magnitude of the axis. For instance, familial trials were conducted to correlate PA between VI, their parents, and siblings [66]. While in [65], the authors studied the PA of children with VI during different segments of the school day from the special school for VI in Xingqing Districts in Yinchuan, China. In this trial, a total of 600 min acceleration was recorded per day, and this input was analyzed within the ActiLife Lifestyle Monitoring System from Actigraph.

Nkechinyere et al. [67] developed software to identify specific daily activities performed by VI and elderly persons. The system uses a wearable accelerometer sensor to collect data that is then submitted to neural network regression (NNR) to characterize each activity as standing, sitting, bending, lying down, or walking. Falls and critical falls are also identified. In this work, the velocity–acceleration measurements are converted to gravity–acceleration by multiplying velocity by sensitivity on each axis. Then, gravity acceleration (G) is calculated using the sum of the squares of the X, Y, and Z-axis in order to remove negative values, and a G target value is representative for individual neural network training. Vibration or shocks could also be determined by thresholds fixed for each axis. Case in point, within the system of Hirano et al., the vibration of a KXR94-2050 3-axis accelerometer sensor was used to allow blind runners to synchronize and match their running tempo with sighted guides (see Figure 2). The algorithm in this system was designed so that when the blind runner's foot touches the floor, a vibration signal was induced in the guide runner's ankle, allowing for synchronization of the race pace [64]. The algorithm was tasked with identifying foot strikes using a low-pass filter applied to samples. The peak acceleration values caused by foot strikes were detected and sent as vibrotactile feedback through a transducer. An acceleration threshold value (4.74 m/s2) was previously settled upon by trial.

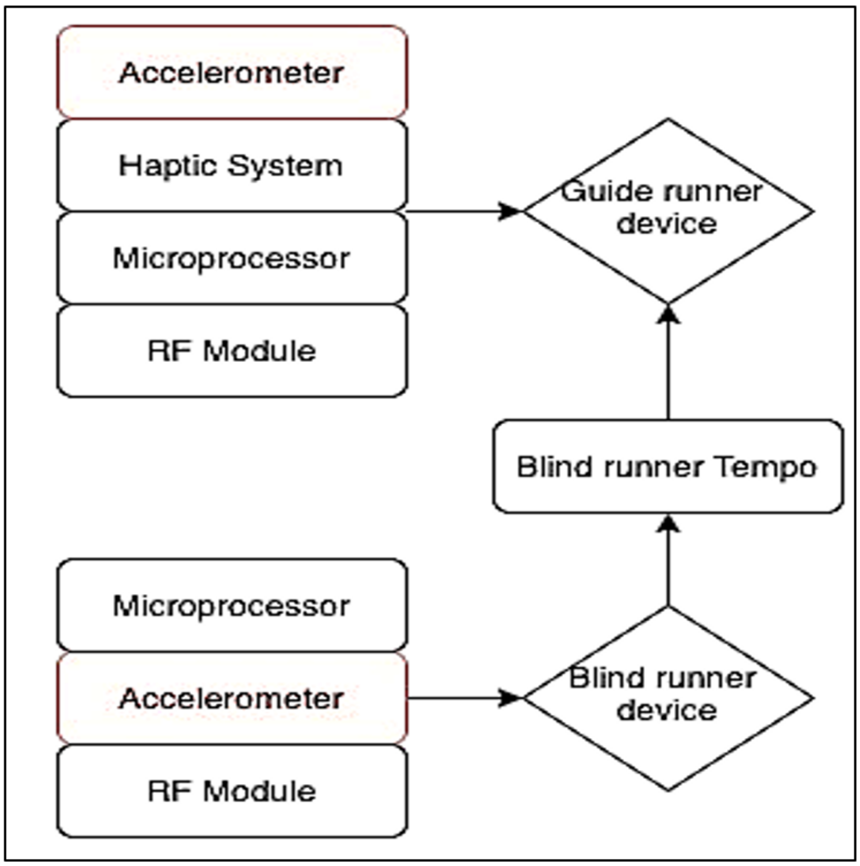

Figure 3.2: Representation of the algorithm for synchronized running proposed by [64]

The work of [59] presents the design and usage of two assistive technologies for VIP that use an ADXL345 accelerometer: a vibrotactile belt and a stereovision system. The vibrotactile belt (NavBelt modified [58]) was connected to ultrasonic sensors (LV-MaxSonar-EZ0) and to the accelerometer. The acceleration values were used to detect and eradicate unnecessary vibrations when detecting user motion, returning user movement and velocity information. The motion and velocity of a user can be recognized using acceleration by detecting stationary periods with the Zero Velocity Update algorithm [18].

3.3.2 Gyroscope

A gyroscope measures angular velocity: the rate of change of the sensor's orientation. Thus, the integration of gyroscope measurements provides information about the orientation of the sensor. Four articles reported using gyroscope input for different roles within sensor fusion, as shown in Table 2.

Table 3.2: Table 2. Summary of reviewed articles in the gyroscope section.

Role	IMU	Sensor Fusion	RE	Ref.
Measure the tilt angle	MPU-6050	Ultrasonic sensor, GPS	0.2–0.5 FA/m	[69]
Detect rotation and movements	MPU 6050	Ultrasonic sensor, GPS	1–7 cm	[70]
Track the direction of gravity, orientation	Smartphone IMU	Camera	-	[71]
Sweeping velocity	Re Sense	Camera	-	[72]

RE = Reported Errors.

In what can be considered a "rehabilitation" application, the authors of [72] used the gyroscope information to characterize long white cane usage in VI volunteers. In their system, the velocity of the cane's sweeping movement was obtained by analyzing the gyroscope's Z-axis signal. The sweeping frequency corresponded to the number of complete sweep cycles performed per second. The sweeping speed was defined as the angular velocity during the sweeping period. In addition, the authors experimented with grasping characteristics based on the positions of the thumb and index finger. They added an optoelectronic motion tracking system (QTM/Oqus, Qualisys AB) to obtain accurate cane orientation angles related to tilt, grip rotation, and sweeping movement.

On a different device proposed to help blind people detect stairs [69], the gyroscope output was used to determine if a change in the distance between the user's head and the ground was due to head tilt or to the user stepping down or up. The method used an ultrasound sensor to measure the distance between the user's head and the ground. The measured distance was compared to a reference distance that corresponded to the floor. So, to establish the reference distance, the gyroscope measured the α angle (corresponding to the head tilt); therefore, the reference distance was:

$$A = \sin(\alpha) + cos(\alpha) \tag{3.1}$$

where A corresponds to the distance from the head tilt to the floor by trigonometry.

With the gyroscope values, the buzzers also could provide information about the distance from the step as well as the height and depth of the step; in this system, a MPU-6050 IMU was used to obtain the tilt angle. The same sensor was used in [70], where the approach was detecting rotation and movements in an automated smart cane. In this system, a high-frequency sound wave was emitted, and its return was used to calculate the distance to an object. Since the device moves continuously while walking, the bottom sonar sensor was fixed in its initial place to detect high surfaces. The gyroscope values were used to control the servo motor;

when the sensor value deviated from the fixed value, the servo rotated and returned to the initial fixed value. Oommen et al. [71] developed a prototype to aid VI swimmers to train with more independence. The device consisted of a smartphone attached to the waist of the swimmer and Voice Recognition Technology (VRT) as the interface, so the swimmer could manipulate the application communicating to the VRT with waterproof Bluetooth earphones. With the help of the camera facing the bottom of the pool and the gyroscope data from the smartphone, the algorithm alerted the swimmer when the end of the lane was near and when the swimmer drifted sideways. The gyroscope was sampled at a minimum rate of 20 times per second and was used to correct the camera images for swimmer roll during strokes. The inertial measurement was essential to determine the orientation of the device and of the gravity vector in the navigation frame. This meant that camera frames were processed only when the device was parallel to the bottom lines, providing a correct estimation.

3.3.3 Accelerometer and Gyroscope Fusion

Accelerometers and gyroscopes are frequently used together in navigation situations when the position and orientation (i.e., attitude) of a device or person are of interest. Articles that reported using input from both accelerometers and gyroscopes sensors represented 33% of those reviewed. As expected, all dealt with navigation aid applications. The most frequently cited IMU was the MPU-6050 from TDK InvenSense, which has a Digital Motion Processor (DMP) to the fusion of the three-axis accelerometer and three-axis gyroscope; more details are described in Table 3.

Croce et al. [73] designed a system where a smartphone camera was the main sensor, which was used to detect special paths such as colored tapes or a painted line. It was also a tracking system based on the integration of a MPU6500 IMU. The authors used the accelerometer values for “Activity recognition”; the accelerometer covariance along the three axes was analyzed to determine if the user is standing still or walking. For heading estimation (direction of the user), the gyroscope data were used to identify the smartphone reference frame with respect to the navigation frame. To estimate the user position with respect to the navigation frame, the Z-axis of acceleration (vertical acceleration) is analyzed to identify steps, while the minimum and maximum vertical acceleration signals are retrieved for peak detection and zero crossings. These features helped to evaluate cardinality so the algorithm could be reliable with different users and different walking speeds. Displacement (s) was evaluated using the algorithm proposed by Weinberg for MEMs in 2002 [74]:

$$\Delta s = \beta \sqrt[4]{\alpha(k)^M - \alpha(k)^m} \tag{3.2}$$

where $\alpha(k)^M$ is the actual time (k) maximum and $\alpha(k)^m$ is the actual time (k) minimum of vertical accelerations, and β is the average length of a step. Finally, sensor fusion with the Computer Vision and PDR algorithms was done by implementing an Extended Kalman Filter. In this model, other parameters, such as angular velocity and direction of the user velocity, were provided by the IMU for the discrete time state model.

Table 3.3: Table 3. Summary reviewed articles in the accelerometer and gyroscope fusion section.

Role	IMU	Sensor Fusion	RE	Ref.
Pedestrian dead reckoning	MPU-6050	RGB-D camera, GPS	0.41 m	[73]
Motion detection	MPU-6050	RGB camera, ultrasonic sensor	-	[75]
Position estimation and orientation	MPU-6050	CMOS camera, line laser	0.4–1 m	[76]
Fall detection and attitude estimation	Not specified	RGB-D camera, GPS, velocity sensor	-	[77]
Fall detection	Smartphone IMU	Ultrasonic sensor, GPS	10–20 m	[78]
Orientation	MPU-6050	GPS, ultrasonic, and wet floor sensors	-	[79]
Attitude estimation	Not specified	RGB-D camera	-	[80]
Step counting	Not specified	Ultrasonic sensor, GPS	-	[81]
Orientation and Height estimation	Not specified	RGB-D camera	-	[82]
Heading estimation	Not specified	GPS, compass	2.9–1.7 m	[83]
Angular velocity and acceleration	Smartphone IMU	Strain gauges	-	[84]
Pose estimation	LSM9DS1	RGB-D camera	-	[85]
Orientation of the head and hand	BMI055 Bosch	UWB FMCW radar sensor	-	[86]

RE = Reported Errors.

Silva and Wimalaratne [75] used the MPU-6050 inbuilt motion fusion for image deblur processing in an optical obstacle detection belt. This was necessary because the camera's continuous movement on the body causes image blurring. The deblur process was done by providing the approximate trajectory of the camera motion. In addition, Ref. [78] used it to create fall alarms in a proposed prototype of an intelligent walking stick for VI and elderly people. The hardware sensing was composed of ultrasonic sensors and GPS. The IMU module monitors the posture of the crutches in real time and verifies whether the horizontal angle and the acceleration direction of the crutches are normal so that a fall can be detected.

Chen et al. [77] reported another way to detect falls using inertial measurement sensors. Among other characteristics, fall detection using altitude estimation is based on an algorithm that processes values from inertial sensors in real time. The pitch angle represents the Y-axis rotation (body's backward pitch); the roll, the X-axis rotation (body side-slip angle from left to right); and the yaw, the rotation angle around the X-axis (rotation angle of the body from left to right). The authors used a Kalman filter algorithm to suppress noise and improve the reliability. Also, they collected additional information (angular velocity and acceleration) to improve the method for user safety.

An assistive device called NavCane [79] was developed to aid VIP finding obstacle-free paths. The NavCane can detect wet floors and obstacles at different levels, and it provides simplified feedback. The inertial sensor input was used to determine the orientation of the cane. To determine the tilt angle, (inclination), they used the gravity vector and its projection on the axes of the accelerometer. Therefore, the tilt's angle of the device was measured using the X and Y-axis inclination of the accelerometer. Then, the inverse sine of the X-axis and inverse cosine of the Y-axis were processed to determine the inclination angle from the measured acceleration. The authors did not indicate which type of IMU they used. In [80], which is an expansion of previous work [87,88], the authors proposed the adaptive ground segmentation method for obstacle avoidance. For this method, they used the camera's attitude angle measured by an IMU, and a corresponding 3D point cloud in the world coordinate system was created and merged with GPS data.

Finally, Fan et al. [66] developed a virtual cane based on an FPGA device (Xilinx ZYNQ-7000). This device is designed to build a map of obstacles in front of the user based on signals emitted by the devices: the laser light provided from the line laser is captured by a CMOS camera. Then, images with a line laser stripe were transferred to the FPGA device. Using the camera's internal and external parameters, FPGA can calculate the true distance between obstacles and the camera. The user must swing the device horizontally so that the vertical light can scan all the objects ahead. Therefore, the IMU tracks the system's pointing angle and relative position with respect to the world coordinate frame. Having both pieces of information, they calculate the distance and shape of obstacles in real time.

In this section, all the authors reported sensor fusion with at least one optical sensor, including also lasers and ultrasonic sensors to obtain information about the surroundings for obstacle detection and navigation [75][76]. The reported navigation error with the lowest value was 0.41 m, as shown in Table 3 by [73]. In this system, PDR is provided by the MPU-6050 and the sensor input includes GPS and an RGB-D camera. This system is the ARIANNA (Path Recognition for Indoor Assisted Navigation with Augmented Perception), which was focused on navigation without obstacle detection.

Other authors proposed the improvement of the functionality of the existing smart vision canes by adding functions such as an emergency call to send a GPS address if the person gets lost, or a remote-control feature to find the stick in case the person loses the stick. The system has an indoor and outdoor guiding system. In indoor systems, the acceleration and gyroscope input is used to count the steps and to verify the directions in which the steps are being produced, so the system can ensure that the person took the exact predefined path to the desired place by using the Adafruit wave kit for feedback to the user [81].

Li et al. proposed a framework to avoid objects in indoor environments [82]. This framework is composed of an RGB-D camera and IMU to detect objects and make a collision-free patch in real time. The acceleration and angular velocity of the IMU are used to obtain the real orientation and height of the camera that are necessary to create a ground segmentation. Decomposing gravity from three-axis accelerations allowed obtaining the camera initial orientation (pitch and roll angles). On the other hand, real-time orientation was calculated by integrating the gyroscope measurements. The initial height estimation was based on the

distance between the chest camera position to the ground. A pedestrian crossing mobile application was developed for the blind by [83]. This system, which could send crossing requests to the signal controller via The National Transportation Communication for Intelligent Transportation System Protocol (NTCIP) without the need for pushing the conventional actuation push button, was a proposal for the traditional accessible pedestrian signal systems. In this system, the inertial measurement united from the smartphone was used to estimate the heading.
An augmented reality system was developed based on radar technology and internal sensors. In this system, measured distances get translated into an interpretable sound rendered in a virtual audio space. The relative orientation of the devices in the head and the hand are computed using the transformation matrix output of both IMUs. At the initial point, the startup of the system initializes the orientation. The azimuth and elevation angles were computed from the resultant matrix in addition to the radar sensor measures. The collected input was the database for the convolution processing [86].

Gill, Seth, and Scheme evaluated the effectiveness of a multi-sensor cane in detecting changes in gait proposed for the elderly and visually impaired; the IOT multi-sensor system included strain gauges to measure load. Different walking conditions, including impaired vision and walking abnormalities due to incorrect cane lengths of the volunteers, were tested by simulating walking abnormalities. The inertial measurement values were used to classify the walking cycle events [84].

A device capable of detecting and locating objects as an object manipulation aid was proposed by [85]. The hand-worn device was composed of an RGB-D camera and an inertial sensor that was used for pose estimation by Depth Enhanced Visual-Inertial Odometry (DVIO). The system provides electro tactile and audio feedback to the user.

3.3.4 Accelerometer, Gyroscope, and Magnetometer Fusion

Magnetometers complement accelerometers by providing sensor heading (orientation around the gravity vector), which is information that accelerometers alone cannot provide. With the fusion of accelerometers, gyroscopes, and magnetometers, the orientation is estimated based on the direction of the magnetic field. In addition, other embedded models that estimate pose can be obtained, which in many cases are more accurate models. In this section, the sensor fusion reported by the authors includes technology such as optical and ultrasonic sensors, BLE beacons, and GPS.

The complementation of the IMU sensor fusion with the mentioned sensors resulted in improvements in navigation system precision. The accuracy obtained with IMU sensors integrated in smartphones is less precise than that obtained with external IMU sensors. For instance, errors on the order of meters (from 1.5 to 6 m) were registered with internal smartphone sensors, while, with external sensors, errors decreased in the order of centimeters (6.17 to 104 cm). This is also attributed to sensor fusion (see Table 4).

Table 3.4: Table 4. Summary reviewed articles in the accelerometer, gyroscope, and magnetometer fusion section.

Role	IMU	Sensor Fusion	RE	Ref.
Device and pose estimation	VN-100 IMU/AHRS	RGB-D camera	0.2 m	[89]
Step counting, body orientation	Smartphone IMU	Barometer	-	[90]
Attitude estimation and orientation	Smartphone IMU	Beacons, GPS	5–6 m	[91]
Pedestrian dead reckoning	Smartphone IMU	Beacons	1.5–2 m	[30]
Body orientation	BNO-055	Optical flow sensors, UWB	0.5 m	[92]
Path calculation	Not specified	RGB camera, ultrasonic sensor	-	[93]
Acceleration and angular rate	Xsens IMU	RGB camera, line laser	6.17 cm	[94]
Tracking the head and body movement	LPMS-CURS2	RGB camera, structure sensor PS1080	25–104 cm	[95]
Detect the right edge of the road	Smartphone IMU	RGB-D camera, GPS	-	[96]
Step counting and Heading estimation	MPU-9250	Ultrasonic sensor, Pi Camera	-	[97]
Head tracking	MPU-9250	GPS/GLONASS and UWB	10–20 cm	[98]
Positioning and step size estimation	Smartphone IMU	N/A	-	[99]
Pose estimation	VN 100 IMU/AHRS	RGB-D Camera	1.5 m	[100]
Absolute orientation	Smartphone IMU	RGB-D Camera	-	[101]

RE = Reported Errors.

A Robotic Navigation Aid (RNA) system described by Zhang and Yen [89] used an RGB-Depth camera and inertial input from an VN-100 IMU/AHRS VectorNav IMU to acquire information about surroundings (Figure 3). In this prototype, the sensor fusion was used for the Visual Inertial Odometry (VIO), which estimates the RNA's pose (orientation and position) so that the path planning node can use the position information to compute desired path and confirm the Desired Direction of Travel that would be used to control the active rolling tip. IMU measurements were used to calculate two of three components from the VIO: For floor detection, the gravity direction $\vec{g}$ and the inclination angle θ of RNA. The IMU state estimation calculates its own pose, velocity, and biases from its own measurements in conjunction with the extracted floor plane data, the tracked features, and the depth data. Then, these parameters are sent to the path planning node. The mode selection is performed automatically on the Human Intent Detection interface. The gyroscope indicates the actual turn angle in motion, which is compared to the expected turn angle from the encoder data (measuring the user's compliance). If both turn angles are equal, this indicates to the system that it intends to use the RNA in its robocane mode instead of its with-cane mode (without robotic aid), expecting a motor-controlled motion of the tip.

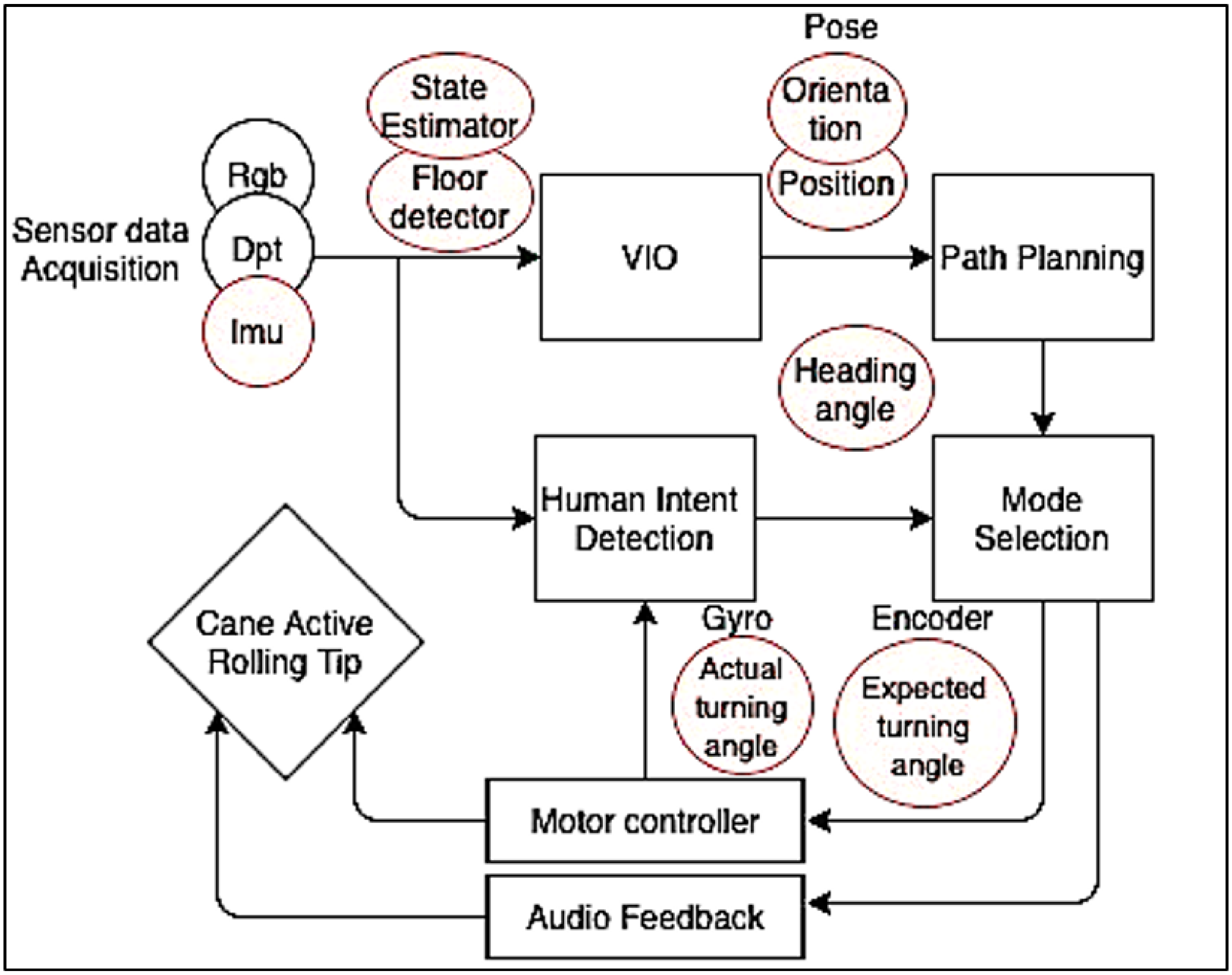

Figure 3.3: Adaptation diagram from the Robotic Navigation Aid system proposed by [89]

The continuation of the previously developed work was also included in this review [85]. This article presented a new method to achieve more accuracy during the navigation. This method is mentioned above, DVIO, which integrates the geometric feature and the visual features of the scene with the inertial data for more acute estimation of the RNA's pose.

Another navigation system was designed to aid VI mobility in places where there is no access to GPS, Bluetooth, or Wi-Fi [90]. The proposed method requires previously recorded paths using the inertial sensors of a smartphone for further guidance. The values obtained from the IMU were used to count steps and determine orientation to calculate route segments, distances, and turns. Vertical acceleration was used to estimate distance because it has a bigger amplitude than does horizontal acceleration. The average step length was calculated from a 20 m walk, and this information served as an input parameter to the program. The average azimuth of the segments was also calculated using the magnetic field perturbation from all three axes of the magnetometer compass. The system is similar to that of [91], who designed a smartphone-based indoor navigation application to aid the VI when using public transport. The system calculates pedestrian dead reckoning based on graphics, and it uses the existing tactile paths for positioning and navigation. Determining the attitude of the smartphone, relative to the user, was crucial to construct the pedestrian dead reckoning algorithm (PDR). The algorithm consisted of computing the orientation quaternion of the local-level frame relative to the body frame. The tilt components, such as roll and pitch (computed with acceleration data) and the heading component, were determined separately (computed with magnetometer data). The quaternion estimation involves a prediction step in which the angular rates (obtained from the gyroscope) are applied. With the step absolute orientation angle, if the step length is known, the change of position can be estimated; as the sensors from smartphones are generally low cost and not specifically designed for navigation, a PDR trajectory needs to be created by developing a map matching algorithm with a graph created with tactile paths (BLE beacons).

An indoor navigation system was developed based on the same sensor input as in [90] (inertial sensor from smartphone and Bluetooth beacons) [30]. A framework was proposed that combines relative position-based learning techniques from IMUs and absolute position based on iBeacons (Figure 4). In this framework, gyroscope data were used to detect relative turns and magnetometer axis fusion with accelerometer data provided heading detection. In addition, an accelerometer provided the adaptive relative position detection. With these three components, it is possible to obtain relative positioning, which, combined with absolute positioning, can provide a final estimated position. Features, including step size, orientation, standby position, roll pitch and yaw, relative turn, movement, and heading angle were all extracted from IMU sensors.

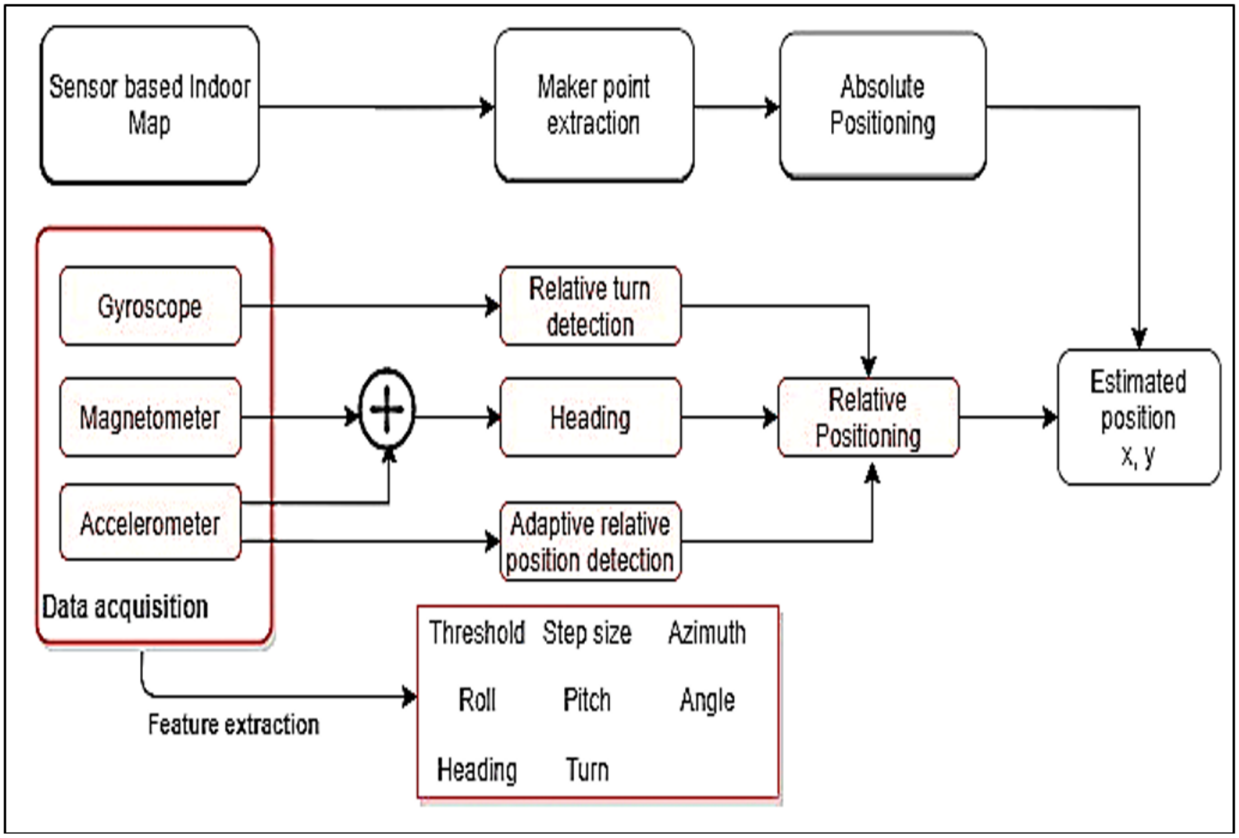

Figure 3.4: Framework of an indoor navigation system for VIP path by [30]

Considering the ability of a VIP to use auditory information to locate sound sources, a Real-Time Localization System (RTLS) for indoor and outdoor sports was designed by Ferrand et al. [92]. The system consists of an accurate 2D position system, a head tracker, and a sound renderer to simulate a virtual sound source. For this system, they used a BNO055 Bosch IMU sensor to determine the orientation of the body, in fusion with an Ultra-Wide Band sensor to provide precise distance measurement and an Optical Flow sensor to determine the velocity of the person when walking. They used the localization of the user to create an augmented reality scene with virtual sound. The software spatializes a sound depending on the position of the user, so the user could identify its own position in the track based on the sound that was being produced. In these systems, the Euler angles from IMU as the head tracker was essential for precision.

Ciabanou et al. [101] developed a system to detect indoor staircases with the help of an RGB-D camera. The algorithm is based on clustering patches from the normal map. To support information provided by the images, an IMU sensor was used to obtain absolute orientation to correct the normal orientation with respect to the depth sensor movement. No additional information about the characteristics of the input or orientation algorithm was provided by the authors, as there are several models to obtain absolute orientation and will be discussed in the next section. In the final algorithm, an important input, “Tangle”, is referred to as a threshold for filtering by orientation. According to the authors, the mean rotation angle of every region was computed.

Simoes et al. [93] created an indoor wearable navigation system for users with visual impairments using computer vision, ultrasonic sensors, and an accelerometer, gyroscope, and magnetometer. The authors didn't provide specific information related to the use of the inertial sensors but declared that during navigation, the path to the next marker was calculated based on the origin point or location point information, and on the orientation. When the system detects a marker, the user's position, direction to other markers, arrival time, and others, are updated and enhanced. They improved the testing OpenCV algorithms to recognize static objects such as doors, walls, etc.

Dang et al. [94] created an assistance system in which the camera, IMU, and world coordinate frames were combined (Figure 5). Since the system combines multiple sensors, a calibration step was done first to estimate the relative position and orientation of each sensor. The height of the system was estimated based on the orientation of the IMU and the laser stripe distance. The motion of the hand was tracked using a Kalman filter. There is one moving interval and two stationary intervals with respect to the person's body. The stationary interval of the IMU sensor was detected when gyroscope values for all three coordinates were approximately zero. The inertial measure was needed for the Kalman filter-based motion tracking algorithm, since the sensors provide the acceleration and angular rate of the system while moving. This algorithm uses the system's initial orientation as the initial value to track the orientation of the system in each swing. Once the orientation of the system was tracked, it was used to determine the pointing angle of the system. For this, the pitch angle was estimated using gravity data. The height also was used to estimate the distance between the person and any obstacle detected.

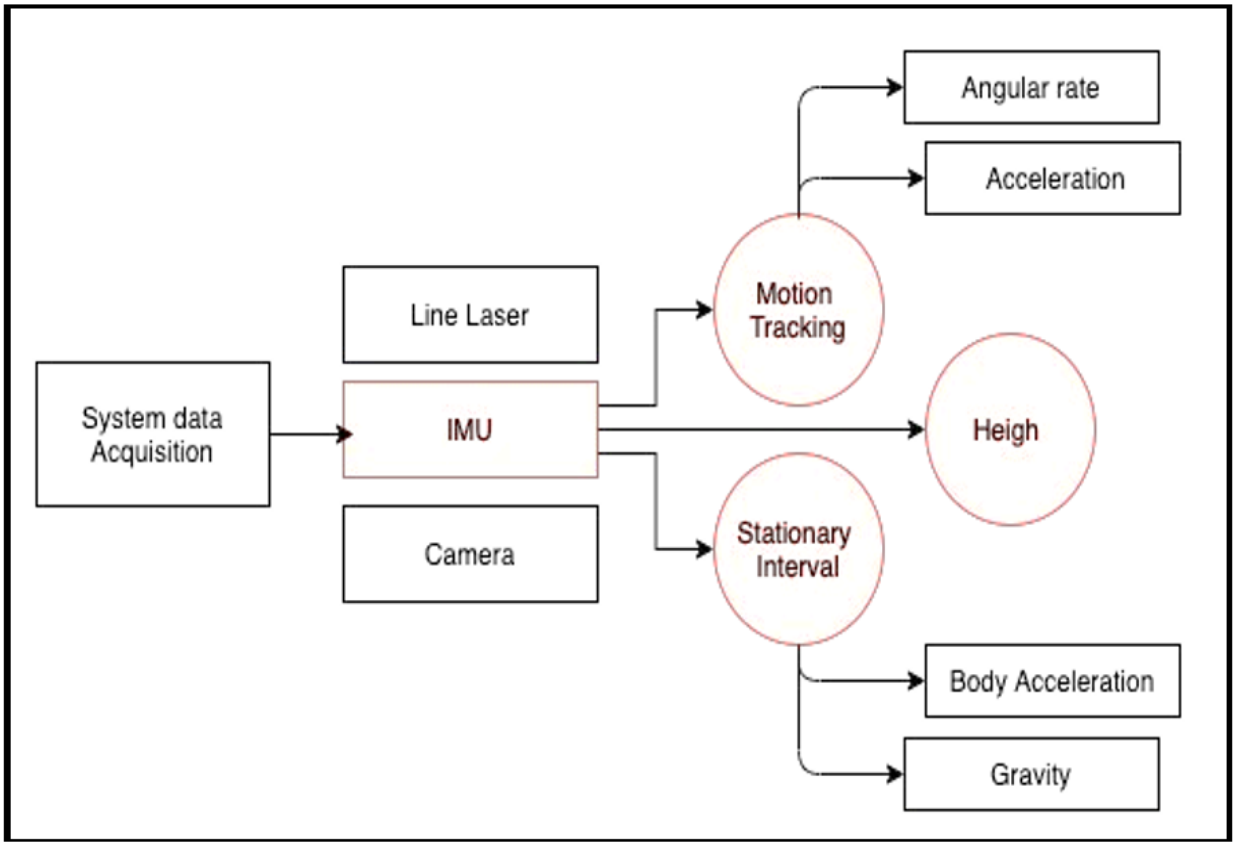

Figure 3.5: Adaptation diagram from the assistance system solution prototype and user's swing motion by [94]

Using a sensory substitution device (SSD) for VI, Botezatu et al. [95] proposed a 3D representation on the space conveyed by means of the hearing and tactile sensors. The IMU sensor (LPMS-CURS2) is used to track the head and body movement. The data acquired from the stereo and structure modules are synchronized with the data provided by the IMU sensor in order to make corrections in the stereo and depth frames. This fusion allows the system to identify the ground plane, doors, and other objects. The inertial measurement was essential to determine device orientation and track gravity orientation so that the camera frames are processed only when the device was parallel to the bottom lines for a correct estimation.

"blindBike" is an application that uses IMU sensor data to assist VIP who bike [96]. The "Road Following" module of this Android application uses 2D computer vision and statistical techniques to create a turn-by-turn route based on GPS map indications. Sensing in this application consists of a smartphone camera, location (GPS) services, microphone, audio output, accelerometer, gyroscope, and compass. The authors do not provide much information about how the inertial measurement units are used in this system. However, they do explain that sensing units are used to detect the right edge of the road and to direct the biker to maintain their route along the right edge as needed. The measured distance of the biker from the estimated right edge of the road determines if the user is on course or not; compass data are analyzed to determine if the bike's heading conforms to what it should be.

Mahida et al. [99] proposed to map the smartphone IMU measurements into 2D local coordinates using the regression-based training of Multi-Layer Perceptron (MLP). Within the three-axis values of the accelerometer, gyroscope, and magnetometer, plus the roll, pitch, and azimuth values from IMU, they trained the algorithm to predict the position of the VI user when holding the phone. They used a previous database that included two types of rooms dividing the spaces into microcells (x,y); the resultant output, predicts an x,y position for indoor location through an smartphone app, as shown in Figure 6.

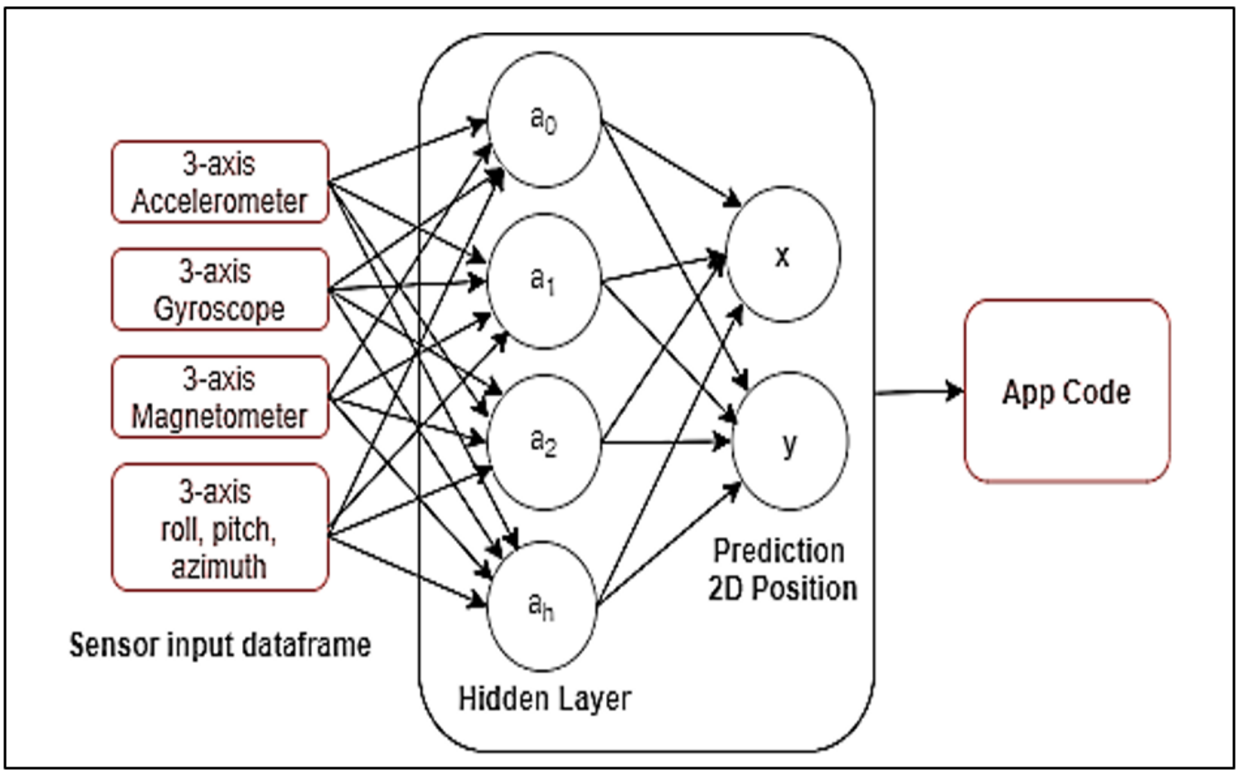

Figure 3.6: MPL network structure for the prediction of x and y position for indoor navigation by [99]

Finally, a wearable low-cost system was developed by [97]. In this system, the authors calculate the magnitude of the acceleration, remove the gravity of the acceleration, and filter the resulting magnitude. The peaks of the magnitude that are above the standard deviation of one were counted as steps. The magnetometer is used to calculate the heading angle. Both are complemented with the obstacle detection system and provide real-time voice command instructions to the user to avoid obstacles. The physical obstacles and the people were constantly being detected by the Pi camera and ultrasonic sensors, respectively.

3.4 Discussion

3.4.1 Technical Analysis of the IMU's Roles

Motion Measurement, Angular Velocity, and Fall Detection

In the first section, most of the authors reported using ActiGraph wearable accelerometers to measure PA. These sensors have been used by the medical community for a long time as activity monitors in clinical trials such as analysis of health psychology and sleeping disorders [102][103], but most of them uses this sensor to measure physical activity [104]. The sensor provides raw three-axis acceleration with a sample ranging from 30 to 100 Hz, which is recorded and then processed. In the processing, these raw data can provide information about the motion activity, such as step counting and positional data (standing, sitting, or lying down). It has been proven that this type of accelerometer may not be sensitive enough to measure very low motion or low physical activity (which is sometimes the case of VIP), suggesting that for more accurate measurement, new classification of activity counts should be developed [105]. Motion detection by accelerometer readings, to establish if a person is moving or not in order to eradicate false vibration, was also applied by Trivedi et al. [59]. Motion readings can also be used for fall detection. Two different methods for fall detection excel in this revision due to the simplicity of the algorithms. Chen et al. [77] propose a threshold-based method where they calculate the acceleration vector sum (AVS) and the angular velocity sum (AVVS) to detect the movement of the user using the equations:

$$AVS = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{3.3}$$

$$AVSS = \sqrt{v_x^2 + v_y^2 + v_z^2} \tag{3.4}$$

the data are collected consecutively while the system is active; it provides a fall alarm if both thresholds exceed the previously settled parameter, and a similar method is reported by Nkechinyere [67]. On the other hand, Ref. [78]used the orientation angles of a placed inertial sensor in order to measure the angle between the crutches (and canes) and the vertical of the world coordinate system, so that when a crutch or cane falls on the ground, an alarm is sent to the main developed system. Another simple method regarding angular velocity was reported by [72]. The sweeping velocity of the long cane was obtained using a gyroscope Z-axis signal (due to configuration of the placed sensor). They used this signal to calculate the frequency and speed of the sweeping. By establishing the quotient between the number of zero-crossings (determine a change of direction in the sweeping cycle) and the product of two times the diagonal duration in seconds, since a complete cycle was calculated from the initial position at the right most point and back from the left most point to the initial position of the subjects, in which the angular velocity is zero.

Orientation/Attitude Estimation and Heading

The relative orientation of two devices can be estimated by computing the transformation matrix output of the IMUs placed in these devices. It starts by initializing the absolute orientation (orientation with respect to the world coordinate system). From this point, the orientation of one device is transformed into the device's coordinate systems, which results in relative orientation. The azimuth and elevation angles can be computed from this matrix representation. Bai et al. [88] used the attitude angles to create an adaptative ground segmentation using a rotation matrix. For this goal, they compute a similar algorithm to that mentioned above, with the difference that the authors harness a depth image to create a 3D point cloud in the world coordinate system, where the reconstructed points xw, yw, and zw are calculated by:

$$x_w, y_w, z_w = zEK^{-1}\begin{bmatrix} u \\ v \\ 1 \end{bmatrix}, \tag{3.5}$$

where

$$E = \begin{bmatrix} \cos\gamma & -\sin\gamma & 0 \\ \sin\gamma & \cos\gamma & 0 \\ 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha \\ 0 & \sin\alpha & \cos\alpha \end{bmatrix}. \tag{3.6}$$

The pixel value of point p(u,v) in the depth image represents the distance between the final point and the camera, which is equal to z. K is the camera intrinsic parameter matrix. The rotation angles of interest are the pitch α and roll γ angles corresponding to the X and Z-axis of the camera.

Absolute orientation can be directly obtained by sensor fusion in 9DOF sensors through Euler output angles [92][98] or quaternion estimation using inertial and magnetic observations, as in the case of [91], where the tilt or inclination components (roll and pitch) were determined separately from the heading component (yaw), so that there would be magnetic disturbances only in the heading value. The gravity direction estimation has an important role in most of the developments that use inertial sensors for PDR or for absolute orientation. The direction of gravity can be considered as the unit vector perpendicular to the local horizontal in a typically northeast plane, pointing vertically downwards. This vertical direction vector is generally time-varying due to the rotation motion when expressed in the device's coordinate system [106]. When the gravity direction is estimated in the device's frame, it can be utilized to decompose any vector. In the case of [70], the gravity direction was used to determine if the device placed in the abdomen of the swimmer was orthogonal to the floor of the pool; in these intervals, the user's position is estimated in frames captured by camera. On the other hand, in the case of [82], the initial orientation of an object was calculated by decomposing gravity from three-axis accelerations, which was represented as:

$$\text{Pitch} = \tan^{-1}\left(\frac{A^2_{X,OUT} + A^2_{Y,OUT}}{A_{Z,OUT}}\right) \tag{3.7}$$

$$\text{Roll} = \tan^{-1}\left(\frac{A_{X,OUT}}{\sqrt{A_{Y,OUT}^2 + A_{Z,OUT}^2}}\right) \tag{3.8}$$

$A_{X,Y,Z,OUT}$ are the accelerations along the X, Y, and Z-axis, subsequently. Since, in theory for real-time orientation, the estimation can be obtained by integrating the output of the gyroscope, as mentioned before, the estimation suffers from the integration of drift over time. The authors used a complementary filter to mitigate the noise and the horizontal acceleration dependency in real-time orientation.
The heading estimation (yaw angle) can be obtained either from inertial sensors only (accelerometer and gyroscope) or accelerometer fusion with magnetometer. In any method, a more precise measure of the roll and pitch angles is easier to obtain than a precise heading measure while calculating orientation angles, which is due to the magnetic disturbance when using a magnetometer or accumulated drift error when using gyroscope values [57][107][108]. These effects can be limited with magnetic perturbation compensation algorithms or with the domain of specific assumptions when treating the sources of error [109]. Although both methods are used according to the hardware selection of the authors, a more precise heading can be obtained when using magnetometer, since the orientation can be estimated based on the direction of the magnetic field [108]. In [97], this method is applied using the next equation for yaw (heading) estimation:

$$\text{Angle} = 180 \times \tan^{-1}(\frac{my}{mx})/\pi \tag{3.9}$$

where my and mx are the magnetometer reading of the Y and X-axis, respectively; to capture the magnetic energy around the surface of a sensor, mechanical calibration is needed.

Positioning and Tracking

Pose estimation is referred to the estimation of both orientation and position by modeling the accelerometer and gyroscope measurements to the dynamics [108]. In dynamic models, for the estimation of states from multiple sensors, the most widely used technique is the Kalman filter, which uses an optimization method for estate estimation [110]. The difference of this method with the Extended Kalman filter is that the Extended method computes filtering estimates in terms of the conditional probability distribution, while the other method can be interpreted as Gauss–Newton optimization of the filtering, using normal distribution in the processed and measured noises of the sensors. The Kalman (KF) and Extended Kalman filtering (EKF) algorithms are used to compute pose and tracking on linear and non-linear models [57][108][110][111]. A Kalman filter-based algorithm was implemented by [?] using the angular rate and accelerations in order to estimate the pose of the system, with the assumption that an accelerometer measures only the gravity when three coordinates of gyroscope values are all near zero, since according to the authors, the acceleration of movement of the visually impaired is small during normal walking. With this presupposition, the pose of the system with respect to the temporary world coordinate frame can be calculated. The Kalman filter-based motion tracking algorithm was also applied by [94]. On the other hand, Croce et al. [73] implemented the Extended Kalman filter. For the state model, the position estimation is calculated on the IMU-based PDR algorithm, using only accelerometer and gyroscope measurements. The user heading, absolute velocity, and coordinates were considered in the measurement model. This KF-based algorithms may not apply to all positioning estimation scenarios; some other non-linear models that are derivatives of the EKF are also suggested by authors to face the estimation accuracy problems of the sensor states [112]. However, the KF-based algorithm is the most frequent method used by the authors of the selected articles discussed in this review. The positioning models can be improved with hardware implementation when fused with local markers as in the graph-based PDR model presented by [91] or the proximity based on visual pattern model by [93]. It can also be improved by using local markers and the implementation of deep learning models [30][99].

3.4.2 Usability

As mentioned in the introduction, an important factor constraining the development of systems to aid the VI is the acceptance of these technologies by the visually impaired community. The following section summarizes information from the research articles presented in this systematic review that pertains to the participation of VIP in tests of proposed systems. Apart from the six articles focused on the measurement of PA, which are based on the participation of VI; only eleven of the 34 remaining articles summarized in the review tested proposed systems with VI volunteers or include VI during their experimental phase [64][67][72][73][79][80][91][92][93][95][98]. Three reported tests used blindfolded (BF) volunteers [59][89][97], and one used both VIP and BF [90]. There is elevated participation of VI in the Bai et al. [80] and Meshram et al. [79] papers. However, most of the authors did not include (or mention) usability questionnaires or user feedback after the usability testing; comments about the user-centered approach are shown in Table 5.

Table 3.5: Table 4. Summary of the visually impaired participation and usability discussion.

Visually Impaired Subjects	Usability Test	Usability Questionnaire	Commentary	Ref.
7	Yes	No	Subjects were participants on the blind marathon sponsored by Japan Blind Marathon Association.	[64]
1	No	No	-	[67]
10	N/A	No	Subjects recruited through the foundation Access for All (Swiss nonprofit organization).	[72]
No described	Yes	No	-	[73]
60	Yes	No	There were 30 subjects who were totally blind and the others had low vision. In addition, the authors involved physiotherapists, rehabilitation workers, and social workers for the development of the usability test.	[79]
20	Yes	Yes	Ten subjects were totally blind and the others were partially sighted. The authors followed the protocol approved by the Beijing Fangshan District Disabled Persons' Federation for recruitment and experiments.	[80]
3	Yes	No	The subjects were student volunteers from the university. A mobility and orientation instructor evaluated their traveling techniques with a long cane to use the application.	[90]
11	Yes	No	The system was implemented and tested at the railway station in Graz, Austria.	[91]
2	Yes	No	-	[92]
10	Yes	Yes	The navigation profile of the users was considerate (height, walking speed, and step distance).	[93]
No described	Yes	Yes	-	[95]
2	Yes	No	-	[98]

RE = Reported Errors.

Concerning usability questionnaires after prototypes testing, only three of the 40 articles reported questionnaires of experience or qualitative feedback after VI participation in the tests, and two reported grading performance or obtaining qualitative feedback from BF participants. The relatively few questionnaires mentioned solicited feedback information such as ease of use or wearability usefulness; response time; independence and localization; sense of safety; and advice for future modifications [93]. Nor did they mention the extent to which the system was helpful and general usability [80]. The paucity of user feedback reported is alarming. VIP and volunteer feedback are important to the development of such systems; targeted users must be considered during the development process or usability may be compromised.

3.4.3 Field of Applications

"Navigation and Object recognition" was the most prevalent VIP application and was cited in 38% of systematic review articles (15 articles), as shown in Figure 7. A high percentage of articles (40%) in this application did not specify which kind of IMU was used as sensor input; this was likely because algorithms for identifying obstacles were based on camera sensing (67%) and/or ultrasonic or laser sensing (67%), so the authors provided more details about the specification of these sensors. However, IMU fusion sensors (accelerometers and gyroscopes or accelerometers, gyroscopes, and magnetometers) played essential roles in the articles selected in these field of application. The roles vary from motion detection and tracking to pose, attitude, or orientation estimation and step counting or fall detection (see Table 3 and Table 4).

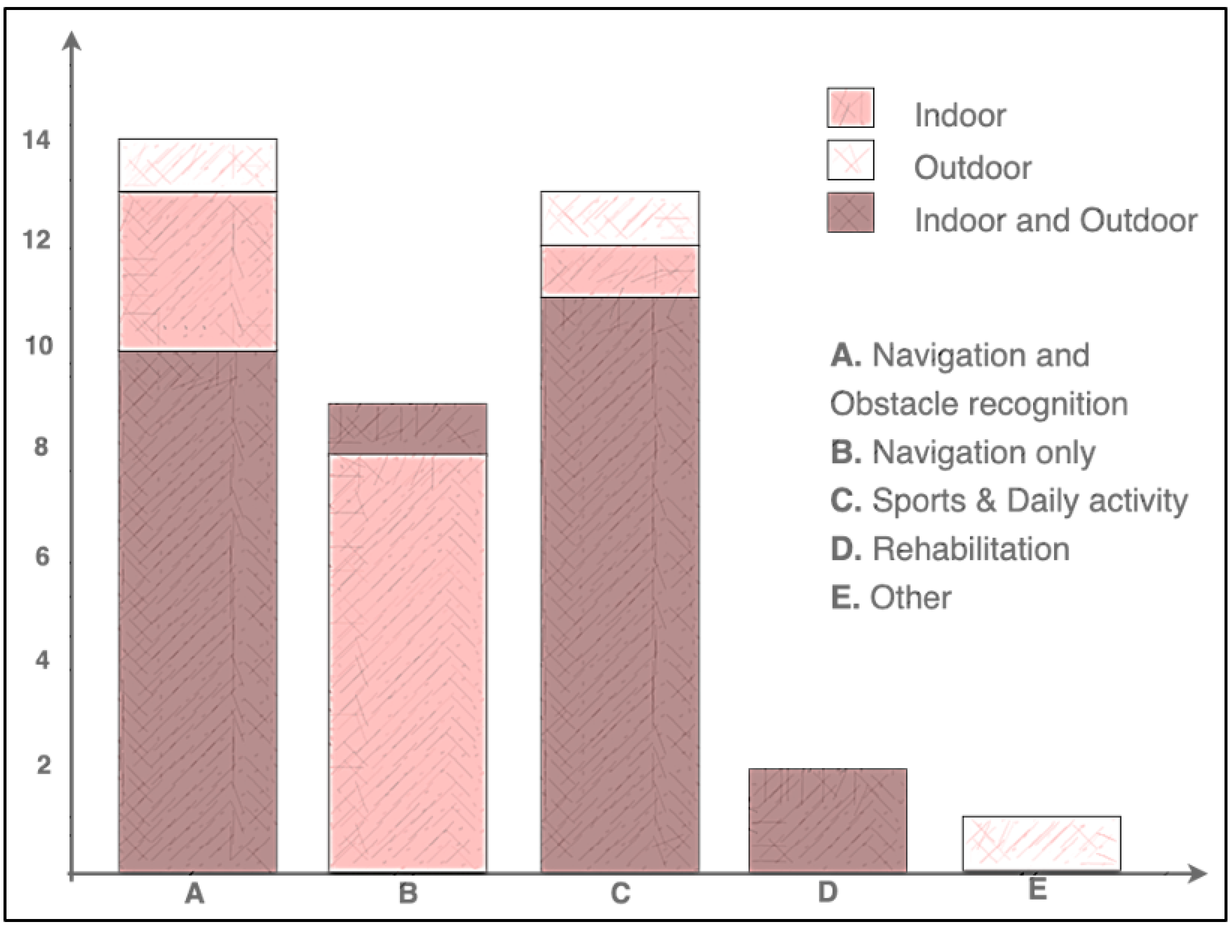

Figure 3.7: Distribution of the articles selected in the systematic review according to the fields of application.

"Navigation only" was the second most cited field of application and was represented in 23%

of the reviewed articles. Researchers tended to use IMUs for several tracking purposes in the systems described: primarily PDR, pose estimation, and step detection. Smartphone IMUs were used as input to algorithms in more than half of the articles to provide "simple architecture" solutions. Only one article reported the use of a single IMU measurement (gyroscope) for input, while 78% developed devices or systems that used three measurement inputs: accelerometer, gyroscope, and magnetometer. The authors of one article did not declare the type of sensor input but referred only to "IMU" input. However, given the nature of the extracted data (absolute orientation), it can be assumed input was from at least two sensors. Although the IMUs listed (ADXL, MPU, LPMS-CURS2, and Xsense) are reported to be more accurate when compared to smartphone IMUs, one article reported the use of smartphone inertial sensing for "Navigation and Object Detection" as compared to five articles in the "Navigation only" application field.
About 33% of the articles were categorized as dealing with "Sports/daily activity" application. We included articles that described or reported research focused on measures of physical activity of VIP, monitoring or improving QoL activities, and systems developed to aid athletes with visual impairments. Research that focuses on monitoring physiological and behavioral patterns with wearable devices, such as inertial sensors, has become more prevalent due to the increasing availability of wearable small devices[113]. Wearable accelerometers are widely used in adapted PA research, since physical inactivity is a serious health issue in VIP [61]. Six articles regarding the measurement of PA among VIP are included, which represent 46% of the articles cited in this section. On the other hand, participation in sports is proven to benefit the VI, not only physically but also personally and socially[114]. The International Blind Sport Federation includes athletics, chess, goalball, soccer, judo, bowling, powerlifting, shooting, showdown, swimming, and Torball as sports. However, climbing, baseball, cricket, golf, sailing, and rowing are also practiced by VIP [115], but only four aid systems related to running, swimming, biking, and roller skating were found in the systematic review.

The IMUs in this application field section were used basically to measure PA by wrist-worn accelerometers to monitor daily life activity by using accelerometer sensor input only. For sports, the roles of the inertial sensors depend on the four identified sports: running (sense the foot movements), biking (detect the right edge of the road), swimming (track the direction of gravity), and roller skating (body orientation and head tracking). Fifteen percent of the articles in this section reported the use of smartphone IMU sensing; 46% reported the use of ActiGraph accelerometers. The Bosch BNO055 and BMI055, the KXR94-2050, and the TDK Inversense MPU-9250 were used in different systems in this application field. For input, 61% of the review articles in this application field used accelerometer data exclusively; one reported using a gyroscope, while four used sensor fusions of acceleration and gyroscope.

Rehabilitation is the systematic process in which VIP are provided with tools to help them deal with their visual impairments with greater independence and self-confidence. These tools include activities such as learning Braille, learning how to use a cane, sightless feeding of themselves, and optimizing the use of residual vision and teaching skills in order to improve visual functioning in daily life [116], as well as other daily activities such as orientation and mobility trained by specialists in rehabilitation [2][4][117]. Only two of the reviewed articles seem to have a rehabilitation approach, although many other designs included in the review can be used in rehabilitation [6][118][119]. However, advances in inertial sensor technology have been critical in assisting in the rehabilitation processes of other physical disabilities such as orthopedic [7][120][121][122][123][124][125]; no further developments have been found to have the specific approach of this important stage in the life of a visually impaired person, even though the importance of this stage has been proven [117][126]. Since the loss of vision leads to functional disabilities and restrains the participation in everyday activities, it limits the individual's autonomy and QoL[127]. Only 13% of the selected articles featured systems to aid the visually impaired people when practicing sports; this is a fact that deserves attention, because as mentioned before, there is a need to promote PA with visual impairments, since inactivity is an alarming and common health issue along them. One last article was considered as "Other" according to the application field division; the authors proposed a system to aid pedestrian signals through a "Virtual Guide Dog" app. Sixty percent of the reviewed articles reported having an indoor and outdoor focus, which relates to the number of articles in the navigation and obstacle detection and the navigation-only applications, while 33% of the articles were focused on developments for indoor only and 8% were focused on outdoor only.

3.4.4 New Avenues of Research and Missing Elements

Artificial Intelligence Integration

The integration of IA architectures was found in twelve of the reviewed assistive technologies; nevertheless, only 17% of these articles (2) used the IMU sensor as input (data feeder). Instead, the rest of the authors used optical sensors from camaras as an algorithm's input. This is because most of the developments were focused on object detection, object recognition, and obstacle avoidance. In this case, several machine learning architectures were tested, such as decision tress [100] and class labeling on computer vision [93]. Deep learning, which consists of networks that have the particularity of extracting features automatically, were applied to the rest of the articles cited in this section, of which Convolutional Neural Networks (CNN) was the most tested architecture[73][77][82][87]. In this review, the authors that implement inertial sensors-based IA applied the architectures to obtain the prediction of a position in 2D local coordinates (x, y) [99] and for recognition of human activities [67]. In the case of the position prediction, an MLP neural network based on regression was tested, reaching an accuracy of 94.51%, which represented a 0.65 m positioning error by using accelerometer, gyroscope, and magnetometer input. This deep neural network model was suggested by the authors as a complementary system for the previous indoor navigation framework, which is also discussed in this review [30].

For human activity recognition, the authors validate a method of neural network regression, achieving 100% accuracy in activity classification using accelerometer input only. IMU data processed as time series is a method for preprocessing the raw data from inertial sensors that has emerged lately, and that helps improve the accuracy of the predictions on human activity recognition [128][129][130][131]. On the other hand, AI based in inertial sensing can be used to improve the parameter estimations in the geometric motion models; also, it can be used to replace the filtering complex models in the non linearity scenarios, for instance to estimate pose and tracking [132]. This would improve the accuracy problems in navigation, where most of the assistive devices of the review are focused. Having said that, it is important to mention that a new avenue of research is the artificial intelligence-based inertial sensing—for instance, for navigation applications.

Biomechanical Analysis

The biomechanical research of visually impaired people is an important research field for injury prevention and for evidence-based rehabilitation methodology. Most of the medical research found in the review was focused on evaluating the physical activity of people with visual impairment; however, visual impairment is usually accompanied by age-related degenerative diseases. That is why a part of the literature focused on visual impairment and blindness is dedicated to study the biomechanical analysis, such as parameters of gait and posture [133][134][135][136]. Analysis of gait parameters using inertial sensors, on the other hand, has been an important topic found in the literature for more than a decade [137]. This literature is focused on the development of algorithms to calculate the stride length and gait velocity as well as analyzing the gait cycles to identify abnormalities, diseases, or changes over time [138][139][140][141] for different medical applications. However, no studies in this review were found linking this technical study area to visual impairment. In fact, in the general literature, a research paper was found featuring a dataset of inertial sensor time series collected from blind walkers created by Manducci and Flores [130]. The authors provided these data to be used by researchers who are interested in personal mobility, since as the authors claimed, there are peculiar characteristics in visually impaired gait. For what we considered this topic, it is a missing element in the literature. In addition, biomechanics and quantification of the long cane for analysis of the motion parameters and performance using inertial sensors is also a research field that can be considered as a new avenue of research and a missing element. Since as shown in the few studies that are found in the literature regarding this topic, a sophisticated 3D motion analysis equipment has been required in both studies to conduct the motion acquisitions for further analysis [72][142]. However, due to the advances in sensor fusion, by using inertial sensors instead of the 3D motion systems and with the right pre-processing and proper interpretation, motion analysis and quantification of the long cane characteristics can be obtained.

3.5 Limitations

A limitation to the present review may be the fact that only three databases were included in the systematic article search. We selected three databases that we consider are relevant to the research topic; perhaps more articles addressing the use of inertial sensors in assistive technologies for visually impaired people are found in the literature but did not comply with the eligibility criteria and thus are not included because they are indexed in other databases. Another limitation lies in the fact that there is no qualitative assessment of the selected articles; instead, all the articles found in the review that met the criteria were included for in-depth analysis, including conferences and short papers. As a result, this review provides a comprehensive systematic review of the recent literature, focusing on the discussion of the use of the inertial sensors.

3.6 Conclusions

A systematic review of research articles was conducted to find system developments that used inertial measurement unit sensors to aid the visually impaired people in assistive technologies. Reviewed articles were categorized according to the type of IMU input used and the role of these IMUs, including pose estimation (position and orientation of a body, an object of a white cane), identification of human motion, i.e., PA and falling, but also specific roles for each application field such as measurement of the sweeping velocity of a white cane, detection of the right edge of the road for blind bikers, or tracking the direction of gravity when swimming. The major approach of the findings was sensor fusion of accelerometers, gyroscopes, and magnetometers (35%), while the less common approach of the findings was the use of gyroscope input (10%). In addition to the IMU data, sensor fusion in most of the articles included GPS (20%) and optical sensors such as RGB-D (16%) and RGB (15%) cameras as ultrasonic sensors (16%). Second, better precision in navigation and positioning estimation can be achieved when there is a fusion of UWB, line lasers, and velocity sensors in hardware when implementing local markers and deep learning architecture in software development. The smaller errors in navigation reported were due to IMU sensor fusion with an RGB camera sensor and the use of external inertial sensors, for instance, MPU-6050 and VN-100 IMU/AHRS instead of a smartphone inertial sensor, which is less precise. In many of the articles summarized, "simple" architecture of the systems to aid the athletes is observed, suggesting that the use of inertial sensors is quite applicable in this area, only more knowledge of the specific activity is needed to create an assistive system. In addition, by using accelerometers only, ActiGraph IMUs were the most commonly used, due to the function of measure of PA. The results indicate that there are new avenues of research within the integration of AI with the use of inertial sensors as feeders to improve the accuracy of the assistive devices developed as navigation assistance. There are also missing elements in the literature such as technological developments to aid the rehabilitation process, the use of inertial sensors for biomechanical analysis in gait and posture parameters, and also biomechanics of usage of the long cane within VIP. In addition, the results have shown that it is necessary to promote as well the inclusion of technology in these biomedical research areas. Finally, a significant limitation evidenced by this review is the fact that the designed aids for the visually impaired lack user-centered designs. Most of the authors used blindfolded persons instead of actual blind persons during the validation of the developments, and only 8% of the reviewed developments included a usability questionnaire for the VI, which should be considered for future research.

Chapter 4

A Proposal of a Motion Measurement System to Support Visually Impaired People

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Abstract

The rehabilitation of a visually impaired person (VIP) is a systematic process where the person is provided with tools that allow them to deal with the impairment to achieve personal autonomy and independence, such as training for the use of the long cane as a tool for orientation and mobility (O&M). This process must be trained personally by specialists, leading to a limitation of human, technological and structural resources in some regions, especially those with economical narrow circumstances. A system to obtain information about the motion of the long cane and the leg using low-cost inertial sensors was developed to provide an overview of quantitative parameters such as sweeping coverage and gait analysis, that are currently visually analyzed during rehabilitation. The system was tested with 10 blindfolded volunteers in laboratory conditions following constant contact, two points touch, and three points touch travel techniques. The results indicate that the quantification system is reliable for measuring grip rotation, safety zone, sweeping amplitude and hand position using orientation angles with an accuracy of around 97.62%. However, a new method or an

improvement of hardware must be developed to improve gait parameters' measurements, since the step length measurement presented a mean accuracy of 94.62%. The system requires further development to be used as an aid in the rehabilitation process of the VIP. Now, it is a simple and low-cost technological aid that has the potential to improve the current practice of O&M.

Keywords: absolute orientation; inertial sensors; orientation and mobility; visually impaired rehabilitation

4.1 Introduction

People with visual impairments face many daily challenges that limit their quality of life. These challenges include basic life activities such as finding and keeping a job, mobility, and displacement, using public transport, among others. When a person is born with a visual disability or suffers from a traumatism or disease that leads to a visual impairment, they must be assisted trough a rehabilitation process. During this rehabilitation process, the person is provided with tools to help them deal with their visual impairments with greater independence and self-confidence. Tools as learning braille, learning how to use a long cane, sightless feeding, also to optimize the use of residual vision and teaching skills in order to improve visual functioning in daily life as well as other daily activities as O&M trained by specialists [2][3][4][5][116][117]. This process of rehabilitation is specialized according to the cognitive capacities of each user, the regular rehabilitation programs worldwide, as reported by the World Blind Union, which includes several stages, such as activities of daily living services, career exploration services, travel-training services/O&M, and others [143]. In several references [117][144][145][146][147][148] the emphasis and importance of the O&M service and training in order to improve the quality of life, is widely emphasized [116][149]. Therefore, there is a specific health discipline in charge of the study, development, and improvement of the O&M training in VIP [150][151][152]. The latest report of the international approaches to rehabilitation programs from the World Blind Union[143] presents two important challenges on which this project was motivated: (1) the limitation of resources to provide basic rehabilitation services and (2) transportation and geographic limitations, where many VIP must displace themselves to other cities in order to access the rehabilitation services which, in some cases, is impossible for some VIP.

A fundamental part of the mobility training is the use of the long cane, the VIP should learn how to hold it correctly, how to grip it, how to walk with it and sweep it in order to detect obstacles, different techniques of exploration, and other parameters according to the complexity of the environment in which the VIP will navigate[153][154]. This training is usually done in person with an O&M specialist, which, as mentioned before, leads to an accessibility problem in rural communities, also it compromises the rehabilitation duration, as well as the number of VIP that can be rehabilitated at the same time. In this training, depending on the scenario there is a recommended technique and according to the complexity and advances of the training, the scenarios will change [118]. However, the parameters for evaluation of the correct use, regardless of the change of scenario, will remain the same; this allows the possibility to register parameters and quantitative values of the motion of the person and the long cane [72], in order to support the O&M training in the rehabilitation processes.

According to the literature, a diversity of technological proposals have been designed for orientation and mobility, such as ETAS (Electronic Travel Aid Systems) [3], focused on obtaining information from the environment and providing it to the visually impaired in order to assist them in autonomous navigation. There have been many attempts to enhance the long cane with technology [76][70][79][89][18]. These systems are developed from technologies such as Global Positioning System, BLE beacons, RFID or radio frequency identification, to obtain information on position and displacement and optical sensors (RGB-D cameras, laser), inertial sensors, speed sensors among others for obtaining information regarding object detection [46][97][92][98][155][40][156]. However, the use of any of these ETAS requires previous O&M training [157][158], leading to an existing gap, which is the development of assistive technologies specifically focused on evaluation and assistance of the training process, so it can be more accessible for users.

Three articles of assistive rehabilitation tools for O&M were found in the literature; Schloerb et al. [159] developed a virtual environment system named BlindAid, created in order to enhance the O&M training. This is a software with haptic and auditory feedback in which the user can virtually visit different unknown places in order to create cognitive mental maps of the representation of these places. Oliveira et al. [160] created a programming language named GoDonnie, to be used as a tool to aid in the resolution of spatial problems involving O&M. This programming language was developed considering the criteria of accessibility and usability for VIP, with the assumption that by using GoDonnie, the user could improve programming and O&M skills, since the users are able to create mental maps of the environments and related objects. On the other hand, Gong et al. [161] developed HeliCoach an O&M training system created to help VIP to train the ability of audio orientation. This training environment is composed of a drone, which moves through 3D space and is used as a sound source. It is composed of a belt with a set of vibration motors for haptic feedback, the belt also contains an BNO055 IMU and six vibration motors controlled by an Arduino DFRobot Leonardo + Xbee. In this system high accuracy indoor localization system is needed for the perspective-driven interaction. For this goal, Ultra-Wide Bandwidth Microwave is used: the system uses four base stations and two tracking tags which are embedded into the drone and the cap of the user, respectively. In comparison to the mentioned developed technologies, the aim of this research was to develop a simple-architecture hardware system using low-cost inertial sensors for data acquisition and test its reliability in the quantitative analysis of the parameters evaluated in the rehabilitation process of VIP by obtaining metrics that the O&M specialists personally examined to aid the rehabilitators during current practice of O&M while training travel techniques. The system can provide information about the hand grip rotation, the safety zone, the hand height during the travel techniques, amplitude and patterns of the sweeping, and gait parameters with a high accuracy using only two inertial sensors.

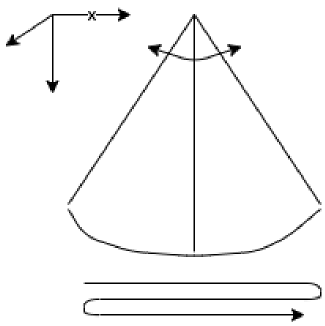
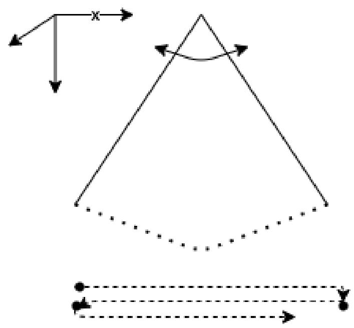
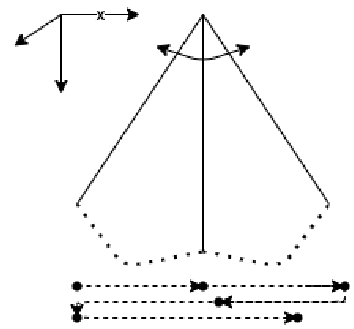
Technologies based on inertial measurement unit sensors (IMU) are used in a large and ever-growing number of applications, such as intelligence guidance, self-driving robots [15][108], full body motion tracking [48][162][52][163] and navigation [46][54][55][99]. An accelerometer measures the external specific force acting on the sensor, which consists of both the sensor's acceleration and the acceleration due to the earth's gravity. A gyroscope measures angular velocity: the rate of change of the sensor's orientation. Thus, the integration of gyroscope measurements provides information about the orientation on the sensor. Magnetometers complement accelerometers by providing sensor heading (orientation around the gravity vector), which is information that accelerometers or gyroscopes cannot provide. With the fusion of accelerometer, gyroscope and magnetometers, the orientation is estimated based on the direction of the magnetic field [108][54]. In the system presented in this paper, the parameters of O&M are calculated using absolute orientation values of the sensor fusion provided by the BNO055 IMU module. Note that the present article is an extended version of [164], where the algorithms to measure amplitude of the sweeping techniques and the orientation of the long cane were tested with 97% and 98% accuracy, respectively.

4.2 Materials and Methods

A tool was developed to evaluate the rehabilitation parameters during the experimental procedure. For the data acquisition an Arduino MKR1010 microprocessor was used with two 9DOF BNO055 IMU Bosch sensors. One sensor placed on the outer side of the leg of each participant and the other on the higher part of a 117 cm long cane. Serial communication was done via I^2C protocol at a sample rate of 0.01 s. In order to remove noise components from the signal, a low pass filtering was performed, with a cutoff frequency of 20 Hz. The microprocessor was wired to a SD card module via SPI protocol and to two push buttons settled as input parameters to control the acquisitions manually. With the use of the Euler roll angle θ_{leg} and the interpretation of step detection according to the values of the filtered absolute orientation, an algorithm was developed to calculate step length using the local coordinates of the sensor placed in the leg. Additionally, to obtain the sweeping metrics with the local coordinates of sensor placed in the cane, the Euler roll ϕ_{cane}, pitch θ_{cane} and yaw γ_{cane} angles were used to provide the grip rotation, the safety zone metrics and sweeping characteristics consecutively.

For the experimental procedure, the acquisitions were performed with 10 blindfolded volunteers. First, the volunteers were instructed and trained for each travel technique while sighted. A floor carrel was marked for the sweep training with an amplitude of around 1 m, they were asked to train each technique walking 20 steps three times. After that, they were blindfolded and asked to perform the travel techniques when displacing around 20 steps in the indicated direction, as described in Table 1. Each acquisition was repeated blindfolded three times, obtaining nine comparative metrics for each participant. The total time and displacement were measured using a 50 m measuring tape and a chronometer. This value served as references values to evaluate the accuracy of the measured gait parameters. Table 1. Description and representation of the top view of the travel techniques for the experimental evaluation of the developed system.

Table 4.1: Table 1. Description and representation of the top view of the travel techniques for the experimental evaluation of the developed system.

Constant Contact Technique (CCT)	Two points touch technique (2PT)	Three points touch technique (3PT)
		
The CCT travel technique consisted in sweeping the long cane in the floor betwen two points with constant contact with an approximate amplitude of 1 meter in order to provide coverage of the walking path.	The 2PT travel technique consisted in sweeping the long cane in the floor betwen two points taking the cane off the ground and creating an arc of around 5 cm, with an approximate amplitude of 1 meter.	The 3PT travel technique consisted in sweeping the long cane in the floor betwen three points. One point in the left, one in the center and one in the rigth. Taking the cane off the ground in each point and creating an arc of around 5 cm.

4.3 Results

4.3.1 Measurement of the Hand Height and the Safety Zone

The Hand Height (HH) and Safety Zone (SZ) are reference parameters to evaluate the reaction distance in O&M, which refers to the warning distance provided by the cane of an object in one's path, the time that is provided by the cane to be warmed about an object or danger [165]. By implementing trigonometrical ratios and using the local coordinates of the sensor, the pitch angleθ_{cane} (which is the transversal axis, equivalent to the angle produced between the floor plane and the long cane) was continuously measured to obtain the height of the hand during and the distance between the tip of the cane and the leg, in the repetitions of the three different travel techniques. Being the HH, the opposite leg of the θ_{cane}, the SZ then is the adjacent leg from the θ_{cane}, as shown in Figure 1.

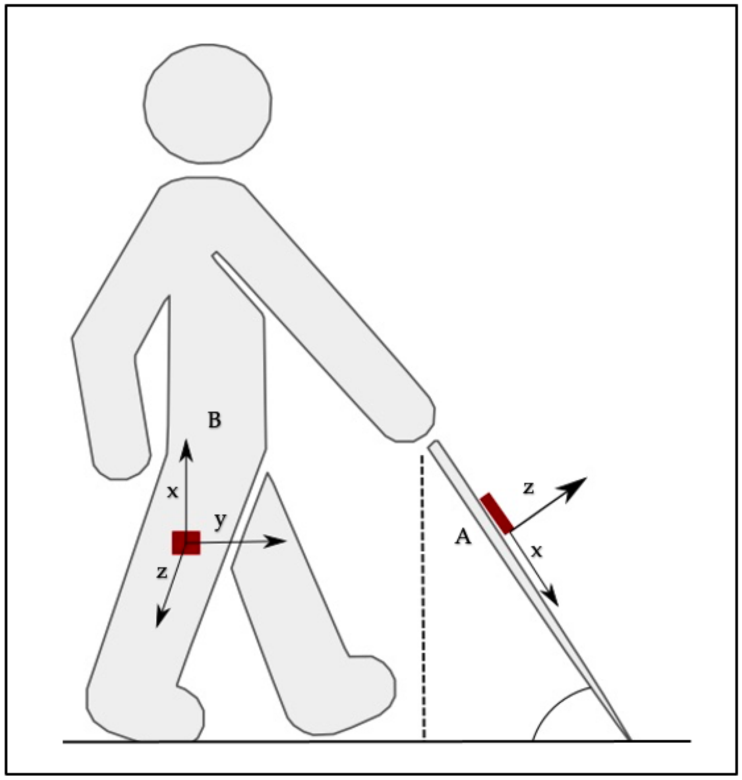


Figure 4.1: Local coordinate system of the sensor placed on the cane (A) and local coordinate system of the sensor placed in the leg (B).

An extract of the measured values for HH and SZ for each subject is presented in Table 2. This value is compared with the real value (RV), which is the self-reported HH and the calculated SZ according to Pythagoras theorem. The mean value is the calculated media of the HH and SZ measurements within the nine travel technique acquisitions. The values of standard deviation (SD) and %Error vary for each subject. The major precision and accuracy obtained was with S01, being the standard deviation of only 1.39 cm, which represents 1.46% of the mean HH and 1.95 cm which represents 2.83% of the mean SZ and the %Error of 0.63% and 1.37%, respectively. Additionally, S09 presented a very low %Error, however a high SD (6.15) which together with S05 presented the less precision on repeatability, the SD being 5.03% of the mean HH and 8.60% of the SZ. On the other hand, the lower accuracy was shown by S06, followed by S07 and S08 with a %Error of 4.62% in the HH and 4.86% in the SZ measurement. Finally, a media accuracy of around 97.62% was obtained by joining all the subjects in both measurements proving that the algorithm applied is reliable to measure these O&M parameters using absolute orientation angles.

4.3.2 Measurement of the Grip Rotation

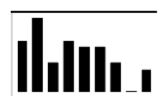
A proper grip was one of the first parameters to be observed by the rehabilitators during the very first stage of the O&M training. With the inertial sensors, is not possible to analyze all the characteristics of the grip, but it is possible to determine the variation of the rotation of

Table 4.2: Table 2. Extract of the measured Hand Height and Safety Zone and statistic characteristics.

	RV cm	Mean cm	SD cm	%Error	RV cm	Mean cm	SD cm	%Error
Hand Height (HH)					Safety Zone (SZ)			
S01	94.00	94.59	1.39	0.63	69.66	68.71	1.95	1.37
S02	89.00	90.17	3.17	1.31	76.00	74.34	3.77	2.18
S03	95.00	94.28	3.37	0.76	68.29	69.35	5.03	1.55
S04	86.00	82.64	2.60	3.90	79.32	82.68	2.59	4.24
S05	94.00	92.56	4.66	1.53	68.66	71.04	6.11	3.47
S06	86.00	82.03	3.75	4.62	79.32	83.17	3.54	4.86
S07	87.00	90.85	2.38	4.43	77.10	73.50	2.86	4.68
S08	88.00	84.13	2.51	4.40	78.23	80.21	4.35	2.54
S09	82.00	81.86	6.15	0.17	83.46	83.08	6.32	0.46
S10	83.00	81.15	2.50	2.23	82.46	84.19	2.39	2.09

the cane which is the consequence of the grip rotation by analyzing the absolute orientation angles, as shown in Table 3. In this table, the SD in degrees for each travel technique by subject was calculated and presented. For this, it was taken into account the total raw data of the roll angle ϕ_{cane} , which according to the local coordinates of the placed sensor represents the rotation of the grip of the user during the development of the travelling techniques. As shown in the Table 3, this value can be representative for technical analysis of the performance of the traveling techniques independently of the stage of and scene in which the user is being rehabilitated. It can also provide a numerical representation to establish what is considered as adequate and acceptable grip rotation according to each travel technique.

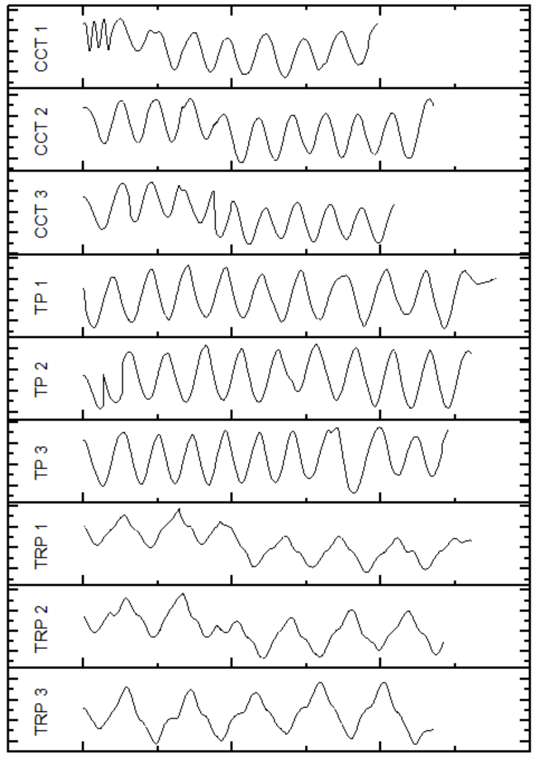
Table 4.3: Table 3. Standard deviation of the measured grip rotation for each subject in the acquisitions of the different travelling techniques.

SD in Degrees														
	S01			S02			S03			S04			S05	
CCT	2PT	3PT	CCT	2PT	3PT	CCT	2PT	3PT	CCT	2PT	3PT	CCT	2PT	3PT
4.55	7.21	5.34	3.44	3.05	2.82	4.34	4.43	2.88	3.72	3.12	2.13	4.45	4.28	3.01
5.68	6.47	4.97	2.76	4.12	3.84	1.88	4.45	3.06	1.93	2.11	2.03	3.67	3.49	3.01
5.31	6.29	4.25	6.14	4.93	3.09	4.84	5.18	2.9	2.66	2.12	2.22	3.43	3.42	3.28
														
	S06			S07			S08			S09			S10	
CCT	2PT	3PT	CCT	2PT	3PT	CCT	2PT	3PT	CCT	2PT	3PT	CCT	2PT	3PT
3.1	3.92	3.92	8.37	5.61	3.92	5.68	3.63	3.5	7.43	7.43	6.19	2.17	2.88	2.47
3.47	3.06	3.06	7.4	6.55	4.72	6.8	4.16	2.91	8.84	7.12	4.4	6.15	2.98	2.41
2.97	2.84	2.84	7.97	6.24	4.5	6.18	5.1	3.11	6.13	7.15	5.75	4.35	3.1	2.21
														

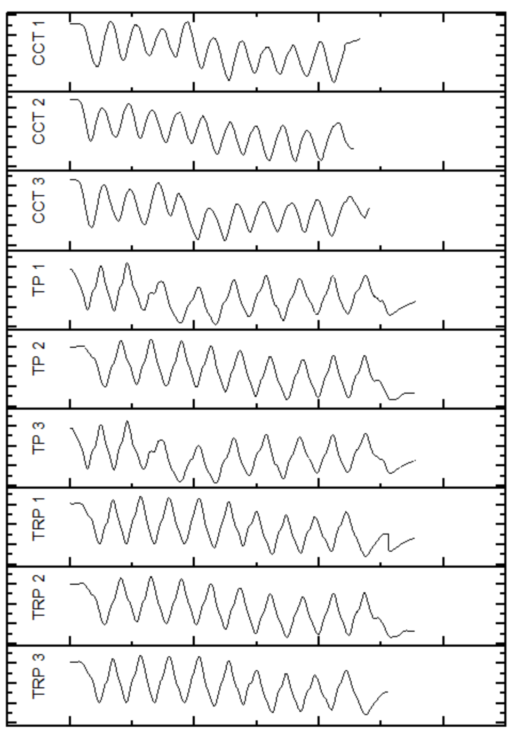
Note that the variation of the values represents the percentage of rotation of the grip during each experiment which means that each column represents how much variation in the rotation of the hand occurred during the experimental acquisition. In the results, it can be observed that S04 and S10 present less grip rotation in the 2P and 3P techniques, which is an indication of a better execution than for instance for S03 and S09. This is direct indication for the specialist to determine which is the acceptable percentage of rotation for each travelling technique and which technique is more appropriate for the visually impaired; it can also allow to have a tracking of the performance during the rehabilitation stages.

4.3.3 Representation of the Sweeping

In [164], it was clearly demonstrated that using absolute orientation angles was reliable to measure the amplitude of the sweepings with the long cane. As described by Blasch and LaGrow [165], the performance of the O&M rehabilitation can be evaluated in terms of "coverage" provided by the long cane, where a full coverage includes, for instance, object preview: the capacity to identify objects in the path of travel with a correct sweeping of the long cane. As the carried out traveling techniques consists of sweeping oscillatory movements, by extracting the motion of the yaw angle γ_{cane} , it is possible to graphically represent the movement of the long cane beside the value of the sweeping amplitude, as shown in Figure 2.



Sweeping preview in 20-steps displacement



Sweeping preview in 20-step displacement

Figure 4.2: Sweeping preview (γ_{cane}) in the 20-step displacement for each travelling technique, S05 (A) and S06 (B).

This graphical representation is indispensable in order to have an estimation of the performance of the travelling techniques while the user is in training, since it is a detailed characterization of the movement of the cane in each millisecond for the dynamic conditions. Additionally, it can help the rehabilitators to evaluate the coverage that is being provided in that moment of the execution of the travelling techniques. As well, for the user to self-correct any lack of coverage with immediate feedback to prevent an accident while correcting the amplitude and execution of the sweeping during the training. It can also help the user and the rehabilitator to quantitatively determinate which is the most appropriate travelling technique for the user. As shown in Figure 2, many differences are observed in the development of the traveling techniques for two subjects (A and B) with the same characteristics. This brings us to one last advantage of this tool, which is the possibility to register the performance of each user during the entire rehabilitation process for future data analysis.

4.3.4 Measurement of Gait Parameters

In terms of coverage, an appropriate gait is crucial for the development of O&M abilities [166], therefore during the O&M training, the gait velocity and the stride length is being constantly visually evaluated by the rehabilitator. With this tool, the method to evaluate the step length for calculating the gait parameters (Stride Length and Gait Velocity) was developed using also absolute orientation angles. With the inertial sensor placed on the outer side of the leg, with the same local coordinates as the sensor placed in the long cane, the pitch angle was used to calculate the step length in a walking cycle and two of the travelling techniques (see Figure 1). The step length was calculated in an algorithm averaging the estimation of the displacement of the leg during the gait cycle following the difference of each peak-to-peak representation of the oscillatory movements of the pitch angle, where each peak represents the higher value of each phase in the gait cycle. Therefore, by knowledge of the leg length of each user, and constantly laying up the values of θ_{legmax} and θ_{legmin}, the step length could be calculated using the following equation:

$$SL = 2 \times \sin\left(\frac{\Theta_{legmax} - \Theta_{legmin}}{2}\right) \times LL \tag{4.1}$$

where SL is the length of the step and LL is the length of the leg of the user. The algorithm is capable of detecting if a step is being executed with the θ_{legmax} and θ_{legmin} thresholds. Table 4 summarizes the measurements obtained in each experiment. Note that the value of the measurement of the SL is an average of the three measurements obtained for each repetition and the mean difference (MD) in centimeters is measured with the resulting three values of the average.

Table 4.4: Table 4. Step length measurement analysis.

Activity	SL m	RSL m	MD cm	SL m	RSL m	MD cm
		S01			S06	
W	0.553	0.500	7.046	0.560	0.546	2.769
CCT	0.517	0.405		0.490	0.443	
3PT	0.577	0.539		0.500	0.478	
		S02			S07	
W	0.553	0.551	2.704	0.678	0.625	4.224
CCT	0.590	0.601		0.731	0.716	
3PT	0.577	0.583		0.664	0.607	
		S03			S08	
W	0.447	0.432	4.937	0.567	0.502	12.370
CCT	0.530	0.534		0.581	0.536	
3PT	0.483	0.542		0.572	0.540	
		S04			S09	
W	0.603	0.592	3.333	0.520	0.502	3.047
CCT	0.563	0.603		0.500	0.536	
3P	0.580	0.550		0.536	0.540	
		S05			S10	
W	0.637	0.498	9.800	0.538	0.505	5.152
CCT	0.603	0.567		0.534	0.566	
3P	0.673	0.554		0.515	0.425	

The difference in centimeters between the actual value and the measured value is very low in most of the cases (2.704 cm–12.370 cm), which indicates that the system is also reliable to estimate the step length, however, in order to calculate traveled distances using this value, it is necessary to set the measurement error and thus dismiss the accumulated errors. This was not possible because there is an extended variation of the mean %Error of the measurement from one subject to other, from 1.07% to 15.06%. The reason for this variation is unknown, perhaps so the proposed method does not estimate hip displacement in the gait cycle. Another reason could be the reliance on the sensor decalibration, however, the accuracy of the absolute angles sensed varies very little with calibration but, as the step length values lie in the order of centimeters, this can be a factor affecting the variation of the %Error, which has a mean of 94.62%.

4.4 Discussion

Kim et al. [72], presented a quantification of the characteristics of long cane usage. In this work, similar parameters are evaluated in terms of the coverage of the travelling techniques in relation to the rotation angles of the movement of the long cane. However, to develop this study, optical tracking cameras were needed in addition to an inertial sensor placed in the long cane. The presented tool allows the dynamic quantification of the characteristics of the movement of the long cane with a lower cost dispositive and complexity and with high precision. With the inertial sensors and the presented metrics, it will be possible to obtain outcome measures as stride rate, gate velocity (meters per minute), and grip characteristics. Additionally, the provided coverage and long mechanics will allow interpretations of the sweeping characteristics as amplitude, frequency and the ability to detect obstacles in the path, as it has been done previously either with more complex acquisition systems [151][167][142], simulated [168] or in some cases manually [169]. The presented measure of the SL can be considered for the estimation of the gait parameters in O&M. Considering the limitations of the method, the most remarkable element of this tool is the fact that the system brings a measurement with the simplicity of one inertial sensor placed in the leg, using only one absolute orientation angle. Most of the algorithms found in the literature considered, beside orientation angles, acceleration values for step detection and calculation of displacement [170], as addition of at least another sensing method, which brings many other limitations and complexity in the development of the algorithm [158]. This article presents a simple method for computing clinically relevant gait parameters, with acceptable precision and accuracy, as in [130]. However, it is a fact that more precision can be obtained implementing a new method considering the details of the swing of the gait cycle or implementing artificial intelligence for instance [130][171]. Currently, a motion analysis device able to evaluate the percentage of coverage provided by a travelling technique according to specific parameters of a user cannot be found in the literature. The RoboCane software [165] was not successfully adopted by the O&M research community in the last decade. This software was designed to calculate the coverage according to direct measurement (manual) of the specific variables of the user. On the other hand, the proposed tool will allow the O&M specialists to have a real estimation of the coverage that the users are providing to themselves in dynamic conditions, which will also help them to be more objective in the evaluation of the O&M training. Among O&M specialists and researchers, it is known that there is no standardization in training methods, and these methods may vary according to the experience of each specialist. That is why research in O&M can also benefit from this tool. The development of the presented tool permits evaluating these mobility parameters independently of the environment complexity in which the training is gradually subjected [172], as it is a low cost portable device. Moreover, further development must be done to obtain more quantification characteristics of the O&M performance of the VIP. By adding one more sensor to the body, for instance, parameters of postural stability and balance analysis can be obtained.

4.5 Conclusions

This article proposed a system able to overview the quantitative parameters of O&M for VIP, which are currently visually analyzed by O&M specialist during rehabilitation, such as sweeping coverage and gait analysis. The proposed tool provides motion analysis of the long cane and the leg by using placed low-cost inertial measurement unit sensors (IMU). The system was tested in laboratory conditions by six blindfolded volunteers following three travel techniques trained by VIP during rehabilitation. The experimental results indicate that this system is reliable for measuring grip rotation, safety zone, sweeping amplitude and hand position using orientation angles with an accuracy of 97%. In terms of future work, a further development is required for the system to be implemented as a rehabilitation aid. Thereby, a more precise method for step length must be obtained, since the mean %Error varies between 1.07% and 15.06% among experiments. Also, more parameters of O&M can be analyzed using IMU's absolute angles, including postural stability and balance analysis. Finally, as the main purpose, the proposed system is a new, simple and low-cost technological aid that that has the potential to improve the current practice of O&M.

Chapter 5

Estimation of Spatio-Temporal Parameters of Gait and Posture of Visually Impaired People

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Abstract

In rehabilitating orientation and mobility (O&M) for visually impaired people (VIP), the measurement of spatio-temporal gait and postural parameters is of specific interest for rehabilitators to assess performance and improvements in independent mobility. In the current practice of rehabilitation worldwide, this assessment is carried out in people with estimates made visually. The objective of this research was to propose a simple architecture based on the use of wearable inertial sensors for quantitative estimation of distance traveled, step detection, gait velocity, step length and postural stability. These parameters were calculated using absolute orientation angles. Two different sensing architectures were tested for gait according to a selected biomechanical model. The validation tests included five different walking tasks. There were nine visually impaired volunteers in real-time acquisitions, where the volunteers walked indoor and outdoor distances at different gait velocities in their residences. The ground truth gait characteristics of the volunteers in five walking tasks and an assessment of the natural posture during the walking tasks are also presented in this article. One of the proposed methods was selected for presenting the lowest absolute error of the calculated parameters in all of the traveling experimentations: 45 walking tasks between 7 and 45 m representing a total of 1039 m walked and 2068 steps; the step length measurement was 4.6 ± 6.7 cm with a mean of 56 cm (11.59 Std) and 1.5 ± 1.6 relative error in step count, which compromised the distance traveled and gait velocity measurements, presenting an absolute error of 1.78 ± 1.80 m and 7.1 ± 7.2 cm/s, respectively. The results suggest that the proposed method and its architecture could be used as a tool for assistive technology designed for O&M training to assess gait parameters and/or navigation, and that a sensor placed in the dorsal area is sufficient to detect noticeable postural changes that compromise heading, inclinations and balancing in walking tasks.

Keywords: inertial sensors; O&M; postural assessment; rehabilitation

5.1 Introduction

Gait analysis plays a vital role in various health applications, but the use of optical motion analysis systems for measuring spatio-temporal gait parameters has limitations such as cost, fragility, lack of portability and resource requirements [166]. Inertial measurement unit (IMU) sensors have emerged as an alternative method for measuring gait parameters, capable of providing both gait and posture measurements by combining IMUs with magnetometers [173]. Among the populations that could benefit from gait measurement, visually impaired people (VIP) stand out. Although electronic navigation aids have been developed for VIP, many of them rely on complex architectures that pose challenges for environmental sensing [146][158]. Smartphone-based inertial sensing, utilizing deep learning methods, requires extensive data for training and may not be tailored specifically to the unique gait patterns of VIP [130]. Furthermore, a recent review highlighted the lack of inertial sensor systems designed for VIP and the scarcity of literature on IMU-based biomechanical analysis in VIP-oriented applications [174]. While wearable inertial sensors have gained attention in clinical research for the gait parameters of people with conditions such as stroke, Parkinson's and multiple sclerosis, there is currently a dearth of studies focusing on VIP biomechanics [175][176]. Existing non-wearable systems for VIP gait analysis have limitations, and there are a lack of user-oriented wearable systems designed specifically for this purpose [166]. Moreover, most spatio-temporal gait parameter analyses for VIP have been developed using motion tracking systems, and the assessment of independent mobility and rehabilitation in orientation and mobility (O&M) typically relies on visual estimates rather than quantitative measurements [177]. Considering the aforementioned gaps, this research aims to propose a simple architecture based on wearable inertial sensors for quantitatively estimating gait and postural parameters in VIP. By utilizing IMUs and magnetometers, this approach seeks to provide accurate and user-friendly gait assessments tailored to the needs of VIP, facilitating their orientation and mobility rehabilitation. The study design includes validation tests with visually impaired volunteers performing various walking tasks, with a focus on assessing gait characteristics and natural posture. By addressing the limitations of current assessment methods and offering a practical solution, this research contributes to the development of assistive technologies for VIP and has the potential to enhance their independent mobility and navigation. This article presents two IMU-based methods for measuring step length (SL), gait velocity (GV), step count (SC) and total displacement (D), and one method for postural assessment (PA). The methods are novel due to their combination of several factors. First, the methods use absolute orientation angle values (leg rotation) during the gait cycle to calculate SL and GV, rather than relying on accelerometry or angular velocity values. Additionally, they apply a gait biomechanical model instead of an abstraction model or a direct integration model to avoid accumulated drift error when calculating each SL and displacement, and this approach maintains the simplicity of the system setup with low computational processing [137]. Second, the methods provide precise real-time measurement of spatio-temporal gait parameters despite using only one or two low-cost wearable inertial sensors. This eliminates the need for post-acquisition gait analysis software to calculate parameters and process data in clinical approaches, as seen in [177]. Third, the methods are designed to be user-oriented and implemented as assistive devices for O&M training, with specific conditions set in the measurement algorithms.

5.2 Materials and Methods

A measuring system comprising two BNO055 (Bosch Sensortec Reutlingen, Kusterdingen, Germany) 9DOF inertial sensors was previously developed [177]. The postural assessment was conducted using a MetaMotionR (MBIENTLAB, Inc., San Francisco, CA, USA) IMU.

5.2.1 Biomechanical Principles

In a gait cycle formed of two consecutive steps, θ (Figure 1A) refers to the inclination angle with respect to the vertical angle, as measured by the inertial sensor. For its part, γ is the rotation angle between the heel strike and heel off during the stance phase of the gait cycle of both legs. However, as the knee does not remain stiff during the gait, γ is, more accurately, the rotation of the virtual segment connecting the hip with the heel. To determine this segment, the inclination, and the length of both of the main subsegments of the leg (thigh and shank), must be known; this adjusted model was the biomechanical model used for the estimation in both of the methods, and it is shown in Figure 1B.

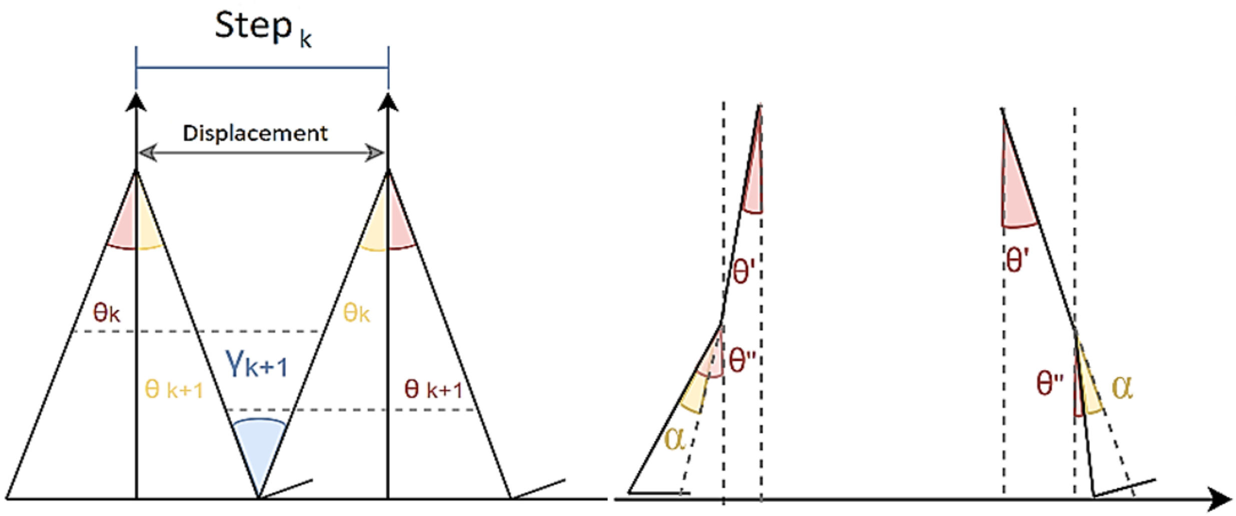

Figure 5.1: Biomechanical models: (A) basic model, (B) knee flexion–extension adjustment

In the two-sensor (TWS) configuration, both inclinations were measured using the IMUs. In the one-sensor configuration (named "thigh sensor" TS), the sagital flexion–extension angles of the knee at heel strike and heel off were extracted from the literature [178][179], and the unknown inclination was calculated relying on the fact that $\alpha = \|\theta' - \theta''\|$, where θ' is the thigh inclination, θ'' is the shank inclination and α is the flexion–extension angle. The rotations denoted by γ led to the displacement of the center of mass in the x-axis of the navigation coordinate frames, which matched the direction of the current step (k). Thus, this displacement is a more accurate approximation of the step length.

5.2.2 Experimental Procedure

This study employed a single-group design with a mixed methods approach. The study was approved by the ethics committee of the Universidad Politécnica de Madrid in October 2020 (ref. ID: 2020000224) and was conducted following the principles of the Declaration of Helsinki. To test both of the methods, nine visually impaired volunteers were recruited via e-mail using the collaboration pool of the National Spanish Blind Association and word of mouth, and the sample selection criteria involved visually impaired people that use either long cane or guide dog assistance. All of the sessions were video recorded, and the volunteers provided their consent after the experimenters read the consent form to them. All of the experiments were conducted at the subjects' residences. The volunteers were instructed to walk in five different conditions with varying velocities, including four indoor experiments and one outdoor experiment. The total displacement for each subject depended on the dimensions of their residence and included the following conditions: Exp1—walking 7–10 m at a normal velocity from point A to point B, Exp2—walking 7–10 m at a fast velocity from point A to point B, Exp3—walking 7–10 m at a slow velocity with short strides from point A to point B, Exp4—walking 14–20 m at a normal velocity with two stops in a hallway from point A to point B and Exp5—walking 60–100 m outdoors from point A to point B. The data collection comprised a total of 2068 steps analyzed over 1039 m to evaluate the accuracy of the two estimation methods.

5.2.3 Parameter Measurement

A single SC algorithm was utilized for both the TWS and THS methods. The algorithm was designed to identify a new step when the leg crossed the vertical position, and to detect the local maximum and local minimum in each inflection point of the rotation angle patterns. Additionally, a straightforward activity recognition algorithm, based on angular velocity, was developed to determine whether the user was moving or not, and thus to prevent the detection of "false steps". More conditions were incorporated, requiring each local maximum to be followed by a local minimum (and vice versa) to count a new step. Regarding SL, the study used the calculated mean accepted value to obtain the correct mean absolute error, along with the registered SC by the volunteers and the defined total displacement. The value of SL was obtained from the rotation γ using the following equation, which applies the cosine law:

$$SL_k = \sqrt{2 \times hh_i^2 - 2 \times hh_{i+1}^2 \cos\cos\gamma_k} \tag{5.1}$$

The length of step k, denoted by SL_k, was calculated using the cosine law by considering the lengths of the hip–heel segments for each leg, denoted by hh_i. The distance measure D refers to the summation of the measured step length for every identified step, as illustrated in Figure 2. This implies that any absolute error in the SL and SC measurements directly influences the D value. The GV for each method was determined by dividing D by the total walking time. The walking time was calculated using the step detection algorithm and compared to the estimated value from the video recordings for computing the mean absolute error, thus ensuring accurate error in GV. The SL and SC measurements can also affect the velocity error.

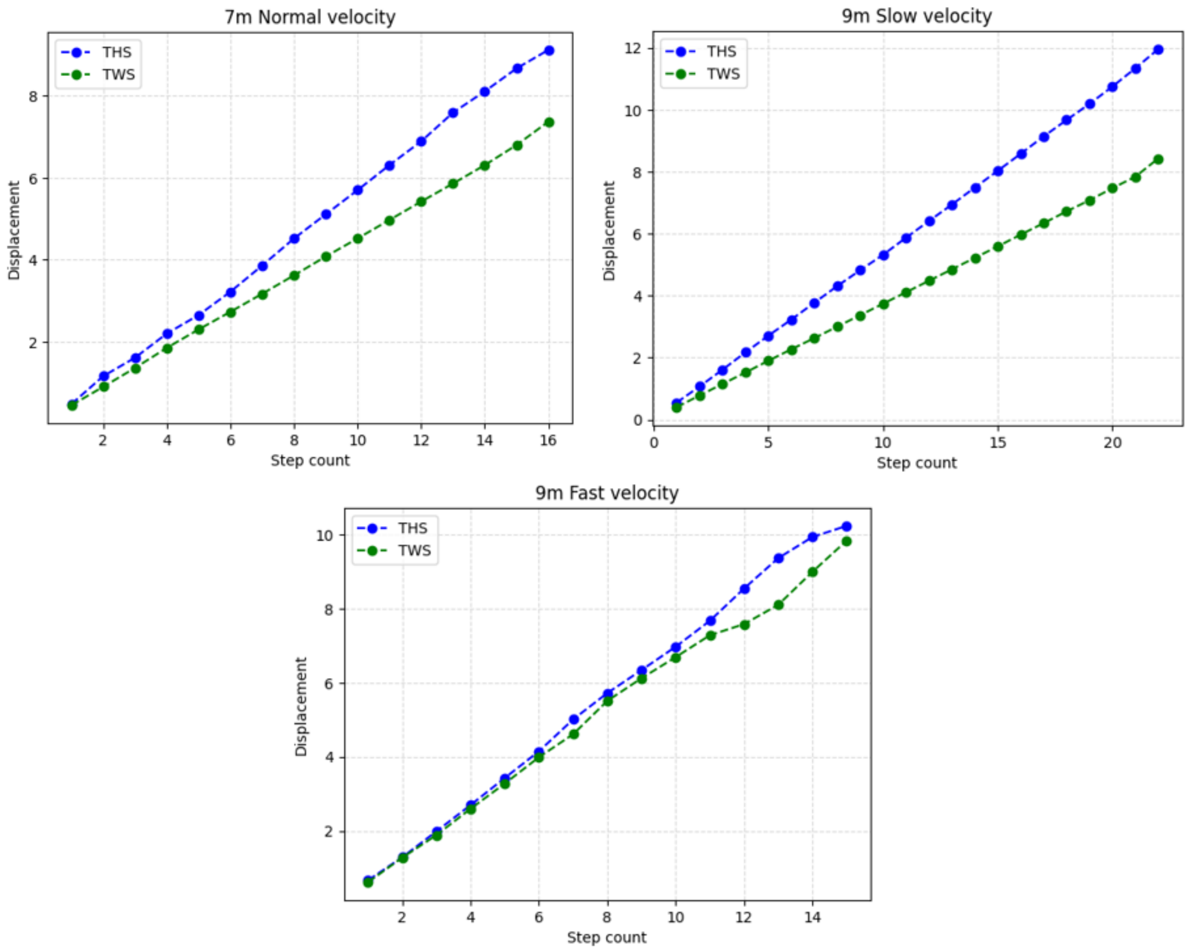

Figure 5.2: Biomechanical models: (A) basic model, (B) knee flexion–extension adjustment

Postural stability refers to the body's ability to maintain balance, and it is often evaluated via postural sway. Postural sway involves constant adjustments of the body's center of gravity on a relatively narrow support base, and personal visual feedback plays a significant role in controlling balance [180]. In this study, postural assessment (PA) was conducted using orientation angles obtained from a sensor placed on the subjects' backs to provide input under dynamic conditions. The approach utilized in this study adheres to the principles of posture monitoring, where a single sensor is positioned at the end of the cervical curve and the beginning of the thoracic curve, as demonstrated in [181]. The 3-angle orientation sensor enables the detection of bending/inclinations, subject tilting to the left and right and postural heading. Although a single method was employed to analyze postural balance, this assessment was performed at a deferred time compared to the other real-time methods that were tested. The standard deviation of the measured roll angle, which indicates the variation in left and right tilting, as well as the standard deviation of the pitch angle, which represents the variation in inclination, were considered in the analysis. In order to confirm that the standard deviations obtained from the orientation angles were capable of detecting significant postural changes that affected heading, inclinations and balance during walking tasks, the researchers conducted a posture evaluation based on the video recordings, as described in [182].

5.3 Results

5.3.1 Subject Information and Gait Characterization

Nine volunteers ranged in age from 23 to 70 years old (M = 51.6, SD = 14.9) The volunteers had been blind for an average of 20.6 years (SD = 14.2) (Table 1). Three participants had residual eyesight (or only bright light perception), self-reported as the recognition of 5–10% shapes. All of the volunteers stated that they could move around Madrid independently with a long cane, and five also had used a guide dog for an average of 5.2 years (4.6 SD). The volunteers had used white canes for an average of 17 years (SD 14.88) and most (8/9) had had at least one O&M training session. Among them, six volunteers had no remaining vision. The gait characteristics of the volunteers were considered as the ground truth (GT) values for the estimation of accuracy during the validation of the methods (Table 2). The values were obtained by measuring the walked distance and counting the steps walked. This assessment was conducted visually and validated via video recording. The average step count from all of the experimental conditions was two steps per meter, with the highest standard deviation observed in the high-velocity (11.36) and outdoor (11.52) conditions.

Table 5.1: Table 1. Socio-demographic characteristics and information concerning the visual impairment of participants.

Age	Gender	Condition	ROV	YOB	RHB	YWGD	YWC	O&M Training
23	M	Optic nerve atrophy	No	11	Yes	1	10	2 weeks
31	M	Retinoblastoma of the optic nerve	No	28	Yes	N/A	17	FS
27	M	Glaucoma	No	6	Yes	2	5	1 day
24	F	Congenital malformation	No	24	Yes	8	19	FS
26	F	Leber's congenital amaurosis	5%	26	Yes	13	16	1 year
23	F	Retinitis pigmentosa	5%	7	Yes	N/A	4	3 months
70	M	Myopia	No	52	No	N/A	55	No
23	F	Bilateral congenital malformation	No	6	Yes	N/A	6	3 months
39	M	Retinitis pigmentosa	10%	26	Yes	2	25	2 months

ROV = rest of vision, **YOB**= years of blindness, **RHB** = rehabilitation, **YWDGs** = years with guide dog, **YWCs** = years with cane, **FSs** = few sessions.

Table 5.2: Table 2. Step length ground truth values.

	S1 (cm)	S2 (cm)	S3 (cm)	S4 (cm)	S5 (cm)	S6 (cm)	S7 (cm)	S8 (cm)	S9 (cm)	Average	SD
Normal velocity	57.2	57.4	43	41.3	56	48.8	37	52.3	61.6	50.48	7.95
High velocity	66.7	66.7	50	38.9	69	50	43	60	71.4	57.37	11.36
Low velocity	55.6	40	33	41.2	47	45.5	34	56.3	50	44.81	7.91
Outdoor normal velocity	76.9	56.6	41	48.9	51	57.1	38	48.4	66.7	53.88	11.52
Step count/m	1.62	1.85	2.68	2.38	1.71	2.01	2.65	1.87	1.63	2.04	0.40

5.3.2 Method Evaluation

Step Count and Step Length

The step count algorithm demonstrated that even with a complete stop (i.e., no rotation angles during several seconds) and slight variations in the heel strike pattern, the step count algorithms worked with precision, resulting in a mean error of 1.48 ± 1.56. The mean absolute error of the measured SL for Experiments 1, 2, 3, 4 and 5, for all nine subjects, was 4.59 ± 3.69 cm for the TWS method and 7.37 ± 4.68 cm for the THS method. Table 3 provides a summary of the mean error for TWS and THS, considering different velocities. The TWS method presents a lower error in all of the experimental conditions. However, THS presents an error lower than 10 cm in all of the experimental conditions (Table 3).

Table 5.3: Table 3. Mean absolute error with standard deviation for step length measurements in TWS THS.

	Normal Velocity	Low Velocity	Fast Velocity	All Velocities	Indoor	Outdoor
THS	8.33 ± 5.00 cm	6.26 ± 4.65 cm	5.58 ± 3.07 cm	7.37 ± 4.68 cm	7.51 ± 4.90 cm	6.82 ± 3.88 cm
TWS	4.20 ± 3.93 cm	5.80 ± 2.51 cm	4.54 ± 4.08 cm	4.59 ± 3.69 cm	5.14 ± 3.89 cm	2.36 ± 1.41 cm

Distance and Gait Velocity

Figure 2 is a representation of the measured distance according to SL and SC of three random subjects with different gait velocities. As can be observed in the graphic and the error results, small stepping and slow velocity might have less accuracy for both methods. The overall mean absolute error for D for all nine subjects in the 1039 m walked was 1.78 ± 1.80 m for the TWS method and 3.20 ± 3.38 m for the THS method. It should be noted that there is a variation in accuracy in the mean values while changing indoor/outdoor conditions; there is an increase in the absolute error for THS from 2.03 ± 1.92 to 7.9 ± 2.74 m, while the TWS error remains nearly unchanged (1 m). In the case of GV measurements, there is negligible variation in error between the THS and TWS methods across all of the experimental conditions. The mean absolute value was 10.40 ± 6.88 cm/s for TWS and 7.03 ± 7.13 cm/s for THS, as both methods employed the same approach for assessing time during gait cycles. Figure 3 depicts the measurement values for two randomly selected subjects across all of the experimental conditions. Figure 3 illustrates how both methods can detect changes in velocity for Experiments 3 and 4, and that the normal velocity measured for Experiments 1, 2, and 3 using the TWS method is more accurate. Overall, the TWS method exhibited higher accuracy but THS presented a lower SD across all experimental conditions and for all spatio-temporal gait parameters measured.

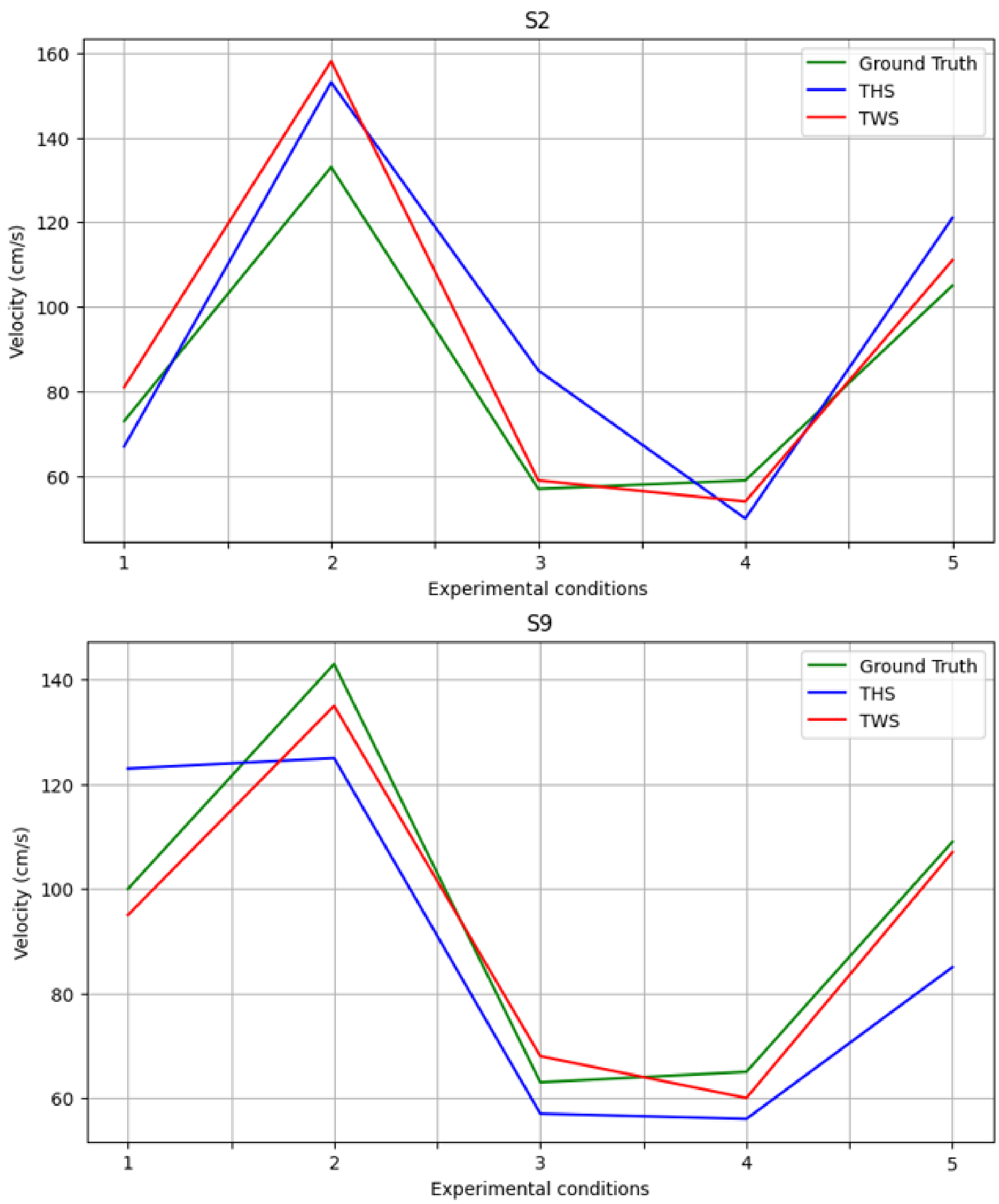

Figure 5.3: Gait velocity measurements in two random subjects for all experimental conditions.

5.3.3 Postural Assessment

Regarding the assessed postural stability, on the one hand, researchers observed noticeable tilts and inclinations during the walking tasks and classified them as binary options (Y/N). On the other hand, they calculated the average standard deviation (SD) of the measured postural angles for each subject and compared it to a threshold value, which was an estimate of a normal angle deviation based on the acquired data from the subject sample. Values exceeding the threshold were categorized as Y and the rest were labeled as N. Based on the analysis of the 45 walking tasks, the % error of the estimation was 38%.

5.4 Discussion

This study aimed to use low-cost sensors and to compare two algorithms using data from IMUs placed on the leg and upper back to estimate parameters related to gait and posture that are typically visually assessed by rehabilitators in O&M rehabilitation of visually impaired. The ultimate objective was to select a method that provided the more accurate estimations, which could allow for proximate quantification of the information that was assessed without quantification methods in the current examination methods during O&M. According to the literature, the proposed methods that use inertial sensors placed on the leg segments concentrate on two approaches for determining gait parameters. One approach involves identifying related variables that correlate with the unknown parameters. Another approach involves direct estimation using biomechanical models or kinematic chains. Frequently, stride length is calculated first by estimating the distance between the feet. The inverted pendulum model, which uses changes in the center of mass height, can also be used. Alternatively, the horizontal acceleration of the feet can be double-integrated to calculate stride length [183]. The approach proposed in this study aims to utilize leg rotation angles with leg segmentation. While the method has shown reasonable accuracy, a limitation is that the method heavily relies on the correct positioning of the sensor on the leg, and as it is based on the orientation angles of the leg during the walking stages in the gait cycle, a bad positioning of the sensor could jeopardize the accuracy of calculations. Nonetheless, depending on leg rotations, this can also be advantageous in terms of detecting steps taken and rest periods more accurately, which can provide better insight for navigation tools. Some researchers have developed accurate methods of detecting steps using acceleration and rotation values in order to reconstruct paths for indoor navigation using deep learning models such as the uni-directional long short-term memory (LSTM) model [184]. This method for real-time assessment could be beneficial for the development of a more complex O&M rehabilitation tool. A large percentage of the visually impaired population is elderly and their gait characteristics may differ from those of non-visually impaired adults. Recent studies have shown that non-visually impaired adults have a mean gait velocity ranging from 1.39 to 1.49 m/s [177], while blind or other VIP exhibit a mean gait velocity between 0.86 and 1.11 m/s [136]. Lower velocity values would likely have bigger standard deviations. Our approach is an acceptable method to measure velocity; however, the error must be reduced if greater accuracy is required in a rehabilitation examination. According to Lim et al. [185], most of the current literature methods focus primarily on other impairments, such as mobility impairments, or different clinical scenarios; none are yet focused on developing methods to analyze gait velocity in visually impaired populations. The results of this study suggest that an automated method for the real-time detection of postural changes to assist in making postural assessments could be achieved with the proposed method. However, it is recommended that the study be expanded to include a larger group of participants to determine a threshold value for different gait velocities; this could result in a lower degree of error.

Finally, by utilizing the input data from the system, including SC, SL, GV, D and PA, it is possible to estimate additional spatio-temporal parameters that may be relevant to O&M rehabilitation, such as cadence or stride rate, which measure the number of steps or double stance per minute [151]. For instance, by applying the same condition used to determine whether a person is walking or not for SC, it is possible to measure the time a user pauses between steps when moving from point A to point B during a displacement task. The results suggest that a balance between general upper body and gait assessment can be achieved with only 2–3 inertial sensors, whereas the current literature may suggest using a greater number of sensors [186]. The results indicate that both the TWS and THS methods could be employed to develop tools for O&M training. However, the TWS method is more appropriate due to its greater accuracy. A rehabilitated gait that promotes enhanced stability can improve balance, emphasizing the importance of early initiation of orientation and mobility (O&M) training to enhance gait, balance and movement [166]. The gait patterns of VIP differ from those without visual impairment. Therefore, assistive technology development and validation should involve insights from VIP. The insufficient involvement of end-users is a limitation of the current literature; development processes must consider targeted users to ensure that usability and accuracy are not compromised [174]. The dataset created in this research could also be beneficial as an input for deep learning models that train quantitative parameters of walking, as evidenced by a recent review [136]; there is a need for research into gait in free-living conditions, i.e., at end-user residences.

5.5 Conclusions

Two different methods were created and tested in five different experimental conditions to assess gait spatio-temporal parameters and to test which method could be more accurate. The results from the TWS configuration were more precise for D, SL, and GV, while the THS configuration produced comparable but slightly less accurate results with greater SD and error, with differences of ± 1.42 m absolute error for D, ± 2.78 m error for SL, and ± 3.37 cm/s error for GV. The addition of a second wearable sensor increases both the computational and hardware cost of TWS, which is the significant architectural difference between the gait estimation methods. Therefore, for measuring the O&M rehabilitation parameters of gait, the TWS method could be more appropriate. However, these results suggest that the THS method, which uses only one sensor, could also be used for other applications in assistive technology when this accuracy range is acceptable. After validating a method for measuring the parameters accurately, the subsequent steps in this research would be to consider developing a feedback system for the user and O&M specialist, as well as the development of a digital platform that considers the end-user's usability as an assistive technology designed for O&M training. This mixed methods approach aimed to validate the proposed method and architecture for O&M training and assess their potential as assistive technologies for VIP.

Chapter 6

Computer Vision-Based Assistance System for Visually Impaired Individuals in Vending Machine Interactions

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Abstract

Vending machines are widely known for their convenient accessibility to a wide range of products, eliminating the need for human assistance. However, visually impaired people often encounter difficulties when it comes to independently selecting, paying for, and retrieving items from these machines due to their heavy reliance on visual cues. This project aimed to address this issue by developing a computer vision-based model that would aid visually impaired people in acquiring products from vending machines. The research involved curating a comprehensive dataset, which consisted of images depicting various types of vending machines and the objects they dispense such as beverages and snacks, also labels for beverages. This dataset served as the foundation for training custom object detection models using the state-of-the-art framework from the YOLO family, applying supervised learning and semi-supervised learning.

By leveraging these models, the aim was to enable the model to accurately identify and locate products within vending machines. To evaluate the performance of the developed model, a series of tests were conducted. The results obtained from these assessments showcased the potential of the model in facilitating a system that could significantly enhance accessibility and independence for VIP who interact with vending machines. The positive outcomes indicated that the model had the ability to successfully identify products within the vending machines, this could lead the users to navigate the purchasing process more effectively. The model demonstrated promising performance and exhibited potential for integration into a larger system aimed at improving accessibility and independence for visually impaired.

Keywords: accessibility, visually impaired people, vending machines.

6.1 Introduction

A Vending Machine (V.M.) is an automated machine that dispenses products in a self-serving-oriented manner. It can distribute snacks, cold beverages, public transit tickets, entertainment things, and others. It is used worldwide because it has many benefits, especially the availability of the products at every time since they are attendant free [207]. The majority of the Vending Machines (V.M.) in public transport and academic environments provide groceries and beverages. The V.M. groceries and beverages products have "all time" availability, being beneficial in the student life where the eating hours can vary. According to recent studies, the current V.M. lacks features that can allow independent selection, payment, and product collection for people with visual impairments [208], since the information of offered products in V.M. can only be known in a visual context. This becomes a problem of accessibility of the self-serving products for the students and employees and people who visit the university campus and have a visual impairment. With this motivation, the aim of this research internship was to develop a tool that could assist visually impaired people in the acquisition of products from vending machines using computer vision models. A. General Concepts Computer vision (C.V.) trains machines to perform the functions of identifying, understanding, and visualizing objects in a scene using Machine Learning (M.L.) and Deep Learning (D.L.) Methods [209][217][218]. Many tasks can be done with computer vision, however, this research focuses on object detection. In object detection, besides classifying different images, it is also necessary to precisely estimate the concepts and locations of objects contained in each image [212]. The problem definition of object detection is to determine where objects are located in a given image (object localization)and which category each object belongs to (object classification). So the pipeline of the traditional object detection models can be mainly divided into three stages: informative region selection, feature extraction, and classification [210][211]. Specific object detection applications include pedestrian detection, people counting, face detection, text detection, pose detection, or number-plate recognition [213]. Different models are typically evaluated according to a Mean Average Precision (MAP) metric. The mean of average precision (MAP) values are calculated over recall values from 0 to 1 [213]. The mAP formula is based on the following sub-metrics: Confusion Matrix, Intersection over Union (IoU)[216], Recall, and Precision. Object detection plays an important role in scene understanding, which is popular in security, transportation, medical, and military use cases. Popular algorithms used to perform object detection include convolutional neural networks such as, Region-Based Convolutional Neural Networks (R-CNN), Fast R-CNN, and You Only Look Once (YOLO). The R-CNN's are in the R-CNN family, while YOLO is part of the single-shot detector family [213]. According to a recent review [219], there are some challenges that are currently faced in O.D., mainly focused on intra-class variation, and a number of categories.

The base of frameworks of generic object detection methods can mainly be categorized into two types; the region proposal-based methods and the regression/classification-based methods. The region proposal-based methods that include R-CNN (Region-based Convolutional Neural Network), SPP-net (Spatial Pyramid Pooling), Fast R-CNN, Faster R-CNN, R-FCN (Region-based Fully Convolutional Network), FPN (Feature Pyramid Network), Mask R-CNN.

The regression/classification-based methods mainly include; MultiBox, AttentionNet, GBCNN (Grid Based CNN), YOLO (You only look once) family, SSD (Single ShotMultiBox Detector), DSSD (Deconvolutional Single Shot Detector) and DSOD (Deeply Supervised Object Detector) [220]. According to other researchers, it can divided into three types; two stages (A network that has a separate module to generate region proposals), single-stage (classify and localize semantic objects in a single shot using dense sampling), and transformer-based detectors [219]. In a recent review, the authors compare compares 3 major image processing algorithms: SSD, Faster R-CNN, and YOLO to find the fastest and most efficient of the three, concluding that out of the three Object Detection Convolutional Neural Networks analyzed, Yolo-v3 shows the best overall performance [224].

6.1.1 Yolo family

The core of the YOLO target detection algorithm is due to the O.D, characteristics: the model's small size and fast calculation speed, this can be achieved because it only needs to put the picture into the network to get the final detection result, and it can also realize the time detection of video. YOLO directly uses the global image for detection, which can encode the global information and reduce the error of detecting the background as the object. The structure can directly output the position and category of the bounding box through the neural network [222]. In 2015, Redmon et al. gave the introduction of the first YOLO version [208]. In the past years, scholars have published several YOLO subsequent versions described as YOLO V2, YOLO V3, YOLO V4, and YOLO V5. There are a few revised-limited versions, such as YOLO-LITE, YOLO V6 and YOLOV7. In this project, transfer learning (use a pre-trained detector and fine-tuning it on a newer dataset) was done with the YOLO V5 small version. YOLO V5 is one of the official state-of-the-art models used for case-specific O.D. tasks and to use in production [225][226]. It is natively implemented in PyTorch. The v5s version is the lightest version for training; Training times for YOLOv5n/s/m/l/x are 1/2/4/6/8 days on a V100 GPU, it is faster in Multi GPU [227]. The YOLO V5, a small version presents a small reduction in Average Precision and more loss in training and validation, however, it allowed us to train and test with speed which was one of the main goals of the internship. For the training, the official YOLOv5 notebook from Ultralytics was used [228].

On the other side, the integration of computer vision in retail reveals the potential of deep learning to swiftly and accurately identify packaged products. As shown by Fuchs, Grundmann

& Fleisch [229], with just six images per product, a commendable 90% accuracy is achieved for image-based product classification (IC), offering a viable alternative to barcode reliance in fast-paced retail scenarios, where perfection may not be imperative. Most of the literature based on computer vision for vending machines is focused in product recognition. For instance, the limitations of existing product recognition methods for intelligent unmanned vending machines (UVMs) in large-scale categories is a large study field. Liu et al., proposed an approach that employs manifold learning to analyze product similarities, constructs a hierarchical multi-granularity label for representation learning, and integrates a hierarchical label object detection network.

The method, validated on the GOODS-85 dataset from actual UVM scenarios, demonstrates effective large-scale product recognition in unmanned retail environments [230]. Using a YOLOv4 deep learning network model, Yin et al., address challenges in achieving higher commodity recognition and counting accuracy in smart vending cabinets, they introduce a novel method for goods recognition and counting in creative cultural product sales cabinets. Experimental results demonstrate an average training accuracy of 98.4% for product recognition and 97.79% for recognizing and counting tasks [235]. O.D developed for retail and vending machines have other motivations, currently, nothing was found with the orientation in interactions, nor accessibility for impaired people. In this article, the accessible vending machine project is introduced: first, a customized dataset of images was gathered and labeled creating a new dataset. The dataset was exported to YOLOv5 format, then the model was trained using YOLOv5 to recognize the objects in the new dataset in several stages to identify the arguments that presented the higher accuracy. The performance of the model was evaluated in all the stages, test inference is presented, including a semi-supervised framework to annotate a video-based dataset. Finally, the model trained with the higher accuracy was deployed.

6.1.2 Methodology

There are six different types of V.M. at Universidad Politécnica de Madrid (Escuela Superior Técnica de Ingenieros de Telecomunicación and Center for Biomedical Technology) and Karlsruhe Institute of Technology (Campus South), the differences are due to the provided product and appearance as shown in the following Figure 1.

Figure 6.1: Vending Machines type according to delivery product and appearance

The Coffee Products V.M (A) has visual information in the selection mode of more than 10 different coffee kinds and can be similar to Ice Cream V.M. (E) and Cold Beverages (C) where there are tags with descriptions of the products. In this kind of V.M. the selection option is either the tag with the description or a button next to the tag. On the other hand, Cold Beverages (B), Snacks and Food (D), and Drink and Snacks V.M. (F) display the products directly for the user to choose and select the required product. In this kind of V.M. for the selection of the product, an alphanumerical code that is written under the product must be input for product selection. The similarities of all the kinds of V.M. are in the segments or parts as shown in Fig. 2

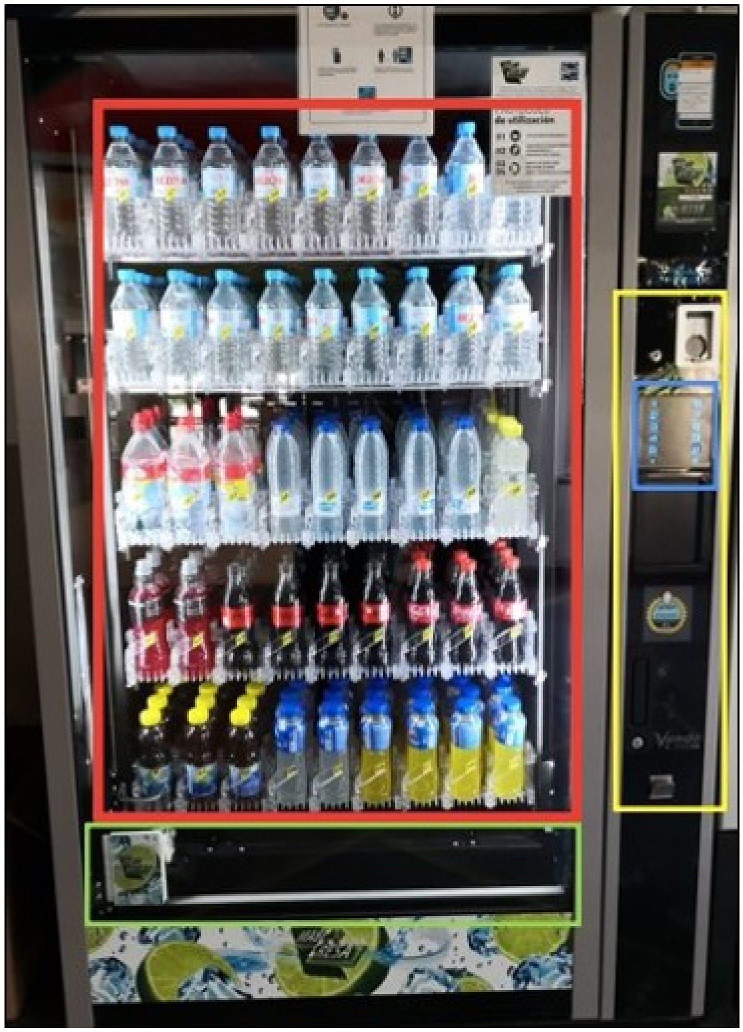

Figure 6.2: Vending Machine parts Red : Products Yellow : Payment section Blue : Selection Code Green : Drop off

Due to the ease of collecting photos on campus, the number of vending machines to which we had access, and due to the limited time to collect the images, three main types of vending machines were finally selected from which the database would be created. Cold Beverages (B), Snacks and Food (D) and Drink and Snacks V.M. (F)

Data Set Creation

Using Open Street Maps Points in the city of Karlsruhe were identified where the dispensing machines were located to take the images, especially images of the campus dispensing machines were taken, about 105 images from Google search were added to the dataset. The first data set contained 204 original images and 105 images from Google search. The images were annotated initially using CVAT, however, due to the facility of the dataset administration, the Roboflow platform was used to manage the image dataset. The original dataset was created with an initial 32 classes as follows:

- Vending Machine type: - drink VM - drinks close VM - drinks snacks VM
- Vending Machine parts: - Payment card - Payment coins - drop off - selection code
- Vending Machine products: - candy gummies - chips – chocolate - chocolate bar - coke pepsi b diet (b for bottled products) - coke pepsi c (c for canned products) - coke pepsi c diet - coke pepsi diet t (t for tags) - coke pepsi t - coke pespi b – cookies - crackers - energetic drink - energetic drink c - juice – nuts - orange soda b - orange soda c - orange soda t - sandwich - soda b - soda c - tea - water - water t.

Due to the availability of the images, there were 4 over-represented classes and 18 underrepresented classes. For the initial training, the original dataset the Yolov5 Ultralytics repository was used in Google Collaboratory. First, with the original datasets, the models were trained with the next arguments: input image size (img), 416, batch size 32, and training epochs from 100 to 300 using our dataset. Then with the arguments known and the mAP obtained in our clean dataset, the original dataset was pre-processed with auto-orient and auto-adjust contrast (Using adaptive Equalization) and augmented with 3 outputs per training example with Noise up to 5% of pixels. The dataset was split into 89% of images for training, 7% for validation, and 4% for testing. Resulting in 672 images for training, 53 images for validation, and 32 images for testing. For the training, a re-augmented dataset was used resulting in 1376 images. Then preprocessed with auto adjust contrast (Using adaptive Equalization) and augmented with 4 outputs per training example with Horizontal flip, and Horizontal Bounding box flip. The dataset was split into 97% of images for training, 2% for validation and 1% for testing. Resulting in 2600 images for training, 53 images for validation, and 32 images for test.

With the augmentation of the images, the values of mAP@05 improved from 0.35 to 0.6. The Precision and recall values also improved and, the box, objectness classification, and their validations were more stable than in the previous results. With these results, the first inference was done with the testing dataset, as it can be observed in Figure 3, the type of vending machines, the parts of vending machines and most of the products could be identified with high accuracy in most of the cases, however in other cases as for tags recognition and some products, the were mistakes and lower accuracy.

6.1.3 Results

With the augmentation of the images, the values of mAP@05 improved from 0.35 to 0.6. The Precision and recall values also improved and, the box, objectness and classification and their validations where more stable than in the previous results. With these results, the first inference was done with the testing dataset, as it can be observed in Figure 3, the type of vending machines, the parts of vending machines and most of the products could be identified with high accuracy in most of the cases, however in other cases as for tags recognition and some products, the were mistakes and lower accuracy.

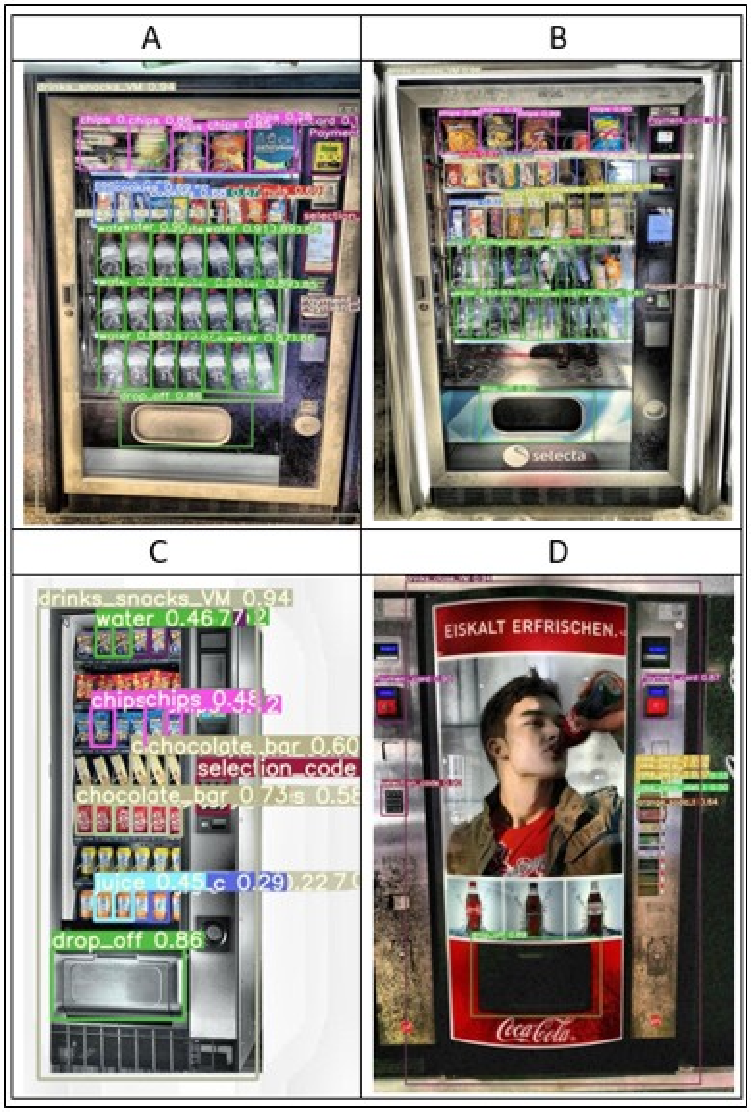

Figure 6.3: Inference image examples of achieved accuracy (32 classes)

Due to class imbalance, the recall, precision, and mAP variated for each class from very low to high values as presented in the next table 1. Due to the differences in mAP for each class, the low precision in tags and some products, for the dataset there was a conversion from 32 classes to 22 classes; All the canned products were categorized in “soda c” and all the classes that contained a tag “t” were categorized into tags the crackers and cookies where also joined. Resulting in 22 classes as follows:

- Vending Machine type: - drink VM - drinks close VM - drinks snacks VM
- Vending Machine parts: - Payment card - Payment coins - drop off - selection code
- Vending Machine products: - candy gummies – chips – chocolate - coke pepsi c - coke pespi b – cookies - energetic drink – juice - nuts – sandwich - soda b - soda c - tag – tea – water.

The model was trained again with the same arguments, with the new 22 classes obtaining the following results: All the values from Precision, Recall, and mAP improved individually for each class and with all the categories. Table 1 shows a comparison of the improvement of the mAP values, in can be observed for instance that with the reduction of the classes, the mAP@0.5 was improved from 0.659 mAP@0.5 to 0.752.

Table 6.1: Comparison of Precision, Recall and maP values for the new classes.

Types	P	R	mAP@.5	mAP@.5:.95
32 classes	0.755	0.632	0.659	0.409
22 classes	0.755	0.736	0.752	0.473

This accuracy was improved by labeling a new batch of images in a semi-supervised framework to improve the overall accuracy of the model.

With these obtained results, the inference was done with the testing dataset, the type of vending machines, the parts of vending machines and most of the products could be identified with high accuracy, in most of the cases higher than 80%. Semi-supervised learning (SSL) is used to improve the predictive performance of learning models using unlabeled data. This framework is particularly used to improve the general model performance when large-scale annotated data is not available. It aims to facilitate the training and deployment of object detectors with the help of a large amount of unlabeled data [16].

At this point, there were around 1376 labeled images with the augmentation in the dataset. However, semi-supervised labeling was done to approximately 1700 images obtained from video recordings. To do this, the model has trained again with the last arguments and configurations (400 e, 32 batch, img size 416), since these results allowed us to obtain the higher mAP. The confusion matrix of the training of this final model is shown in Fig. 4.

The higher accuracy in the predictions are in the three categories of “Types of Vending Machines”, with almost no FP or FN. However, there is a high possibility of obtaining FP and FN in the categories of chocolate vs. cookies (0.17), soda c vs coke pepsi c (0.12), juice vs soda b(0.14), tea vs energetic drink (0.25) and nuts vs cookies (0.45).

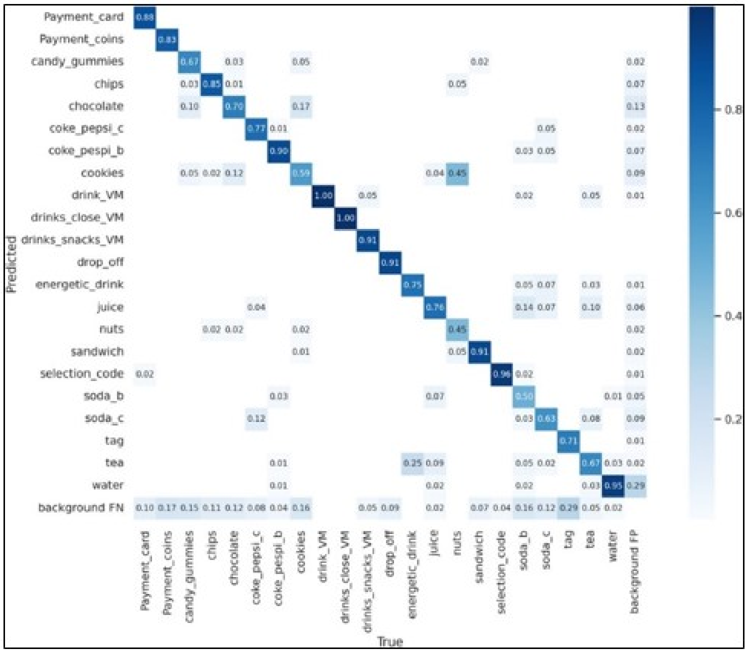

Figure 6.4: Confusion Matrix of the Vending Machine Products prediction in the model used for semi-supervised learning

Comparing, in this model a small increase in mAP values is observed; @0.5 the mAP increased in 10% from almost 70% to almost 80%, @0.95 the mAP stayed the same to almost 50% however with less fluctuation. A higher accuracy was observed in the model used in the semisupervised framework. No FP is observed in the images, on the contrary, the parts of the vending machine are accurately identified, the type of vending machine is identified in both cases with more than 90% confidence, and both “drop off” sections are identified with high and low confidence and all of the products where recognized.

All the images were added to the final dataset, turning in a final of more than 2800 labeled images, however, due to the values of precision of the model and the low confidence thresholds the dataset contained many mistakes in the annotations. For that reason, all the images had to be revised one by one in order to change and remove annotations. In the case of many wrong annotations in an image, the image was eliminated. The new images were obtained from split videos and taken from the camera where added, and the HoloSelecta [223] dataset was included and labeled with the semi-supervised framework and the revised one by one for annotations. For this final dataset, there were 2674 images, with 68,952 annotations. The class balance, as expected maintained the imbalance between the classes, keeping over-representations and under representations, however the instances for each class were 7-10 times higher for the overrepresented classes and 11-28 times higher for some of the underrepresented classes.

Figure 6.5: Inference image examples of achieved accuracy (22 classes) of the model used for semi-supervised learning

For the final training, the final dataset was pre-processed with auto-orient, Resize: Stretch to 416x416, and augmented with 3 outputs per training example with Saturation: Between - 25% and +25%. The dataset was split into 87% of images for training, 9% for validation and 4% for testing. Resulting in 5,500 images for training, 533 images for validation, and 275 images for testing. The results present values of mAP@0.5 were improved to more than 0.8 and the values of mAP@0.95 were improved up to almost 0.7. The Precision and recall values were also improved to up to 90% for both of them. Also, the training and validation curves of box loss, objectness loss and classification loss were more stable than in the previous results Figure 6 shows the confusion matrix of the vending Machine Products prediction in the model training with the final dataset. As it can be observed in the confusion Matrix, the higher accuracy in the predictions is maintained in the three categories of “Types of Vending Machines”, even though the values of predicted versus true slightly lowered, most of the categories improved their accuracy, now there is almost 0 possibility of FP and FN in the confusion of the pairs chocolate vs. cookies, soda c vs coke pepsi c, soda b vs juice, tea vs energetic drink, nuts vs cookies, water, tea, tags, and chocolate.

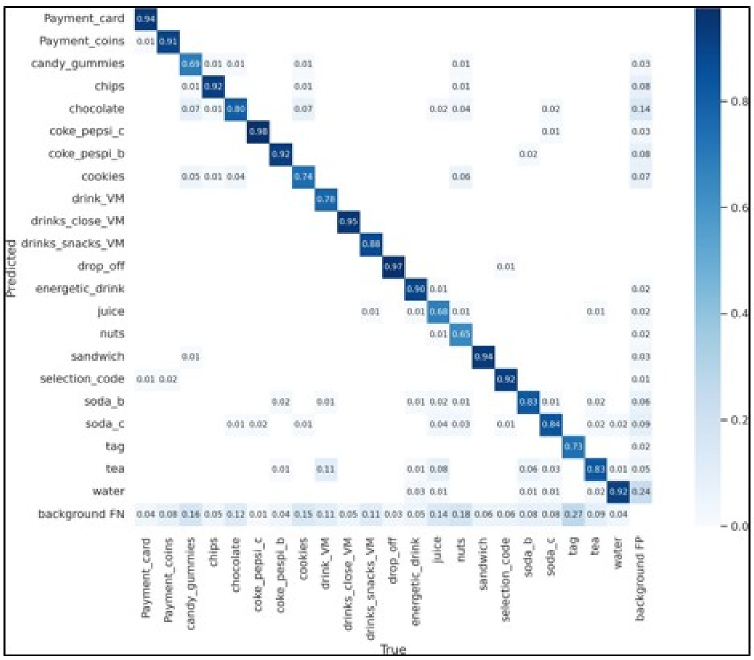

Figure 6.6: Confusion Matrix of the Vending Machine Products prediction in the model training with the final dataset

To have an overview of the summary of prediction results in this model, the F1 Score and the Precision and recall values are presented in Fig 7.

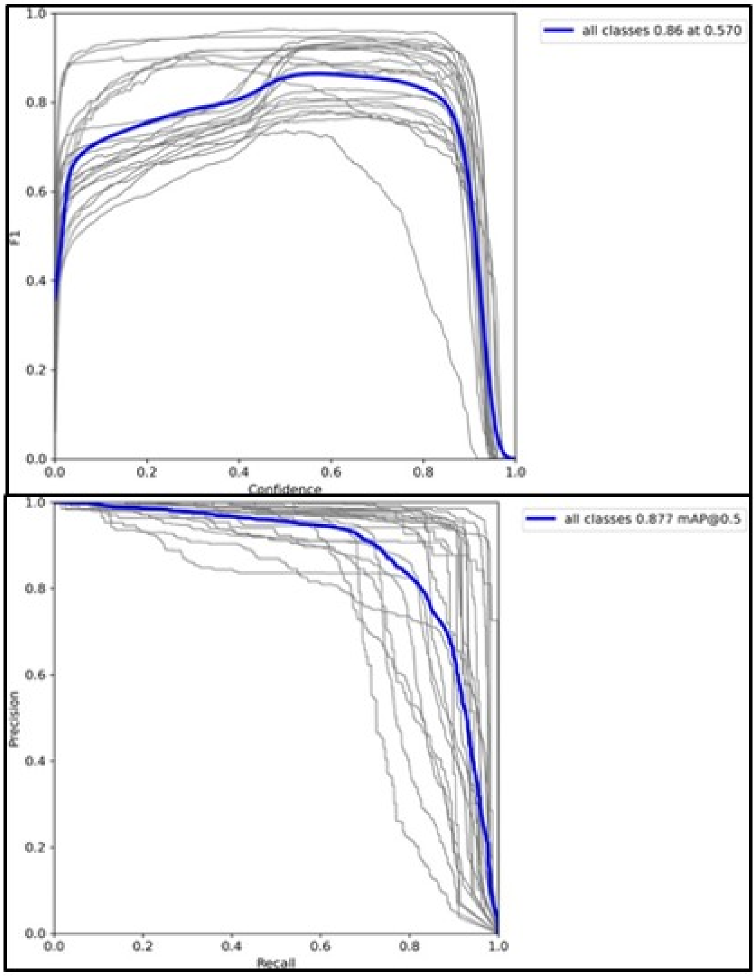

Figure 6.7: (A)F1 vs. Confidence graph (B) Precision vs. Recall graph for all classes in final model

The mAP@0.5 was improved from 0.74 and 0.752 (at 565) to 0.855 and 0.85 (at 0.570). Finally, the recall, precision, and mAP of the 22 classes in the final model are presented in Table 2.

Table 6.2: Comparison of Precision, Recall and maP values for the new classes.

Class	P	R	mAP@ .5	mAP@ .5:.95
all	0.892	0.846	0.877	0.715
Payment card	0.947	0.948	0.971	0.801
Payment coins	0.932	0.911	0.910	0.686
candy gummies	0.795	0.726	0.751	0.605
chips	0.930	0.927	0.927	0.751
chocolate	0.846	0.807	0.830	0.651
coke pepsi c	0.912	0.977	0.946	0.772
coke pespi b	0.94	0.900	0.939	0.742
cookies	0.804	0.777	0.794	0.645
drink VM	0.979	0.716	0.909	0.800
drinks close VM	0.874	0.911	0.963	0.891
drinks snacks VM	0.906	0.863	0.853	0.754
drop off	0.964	0.959	0.972	0.826
energetic drink	0.866	0.906	0.915	0.762
juice	0.931	0.711	0.809	0.674
nuts	0.911	0.679	0.739	0.614
sandwich	0.939	0.922	0.926	0.798
selection code	0.912	0.930	0.935	0.741
soda b	0.896	0.834	0.881	0.702
soda c	0.776	0.832	0.787	0.620
tag	0.917	0.597	0.793	0.499
tea	0.702	0.867	0.799	0.652
water	0.948	0.906	0.939	0.748

6.1.4 Conclusion

A costumed dataset of images was gathered and labeled creating a new dataset that contains a final. Several models were trained using the YOLOv5 notebook until obtaining a final model with 89% Precision, 85% Recall, 88% and 78% mean Average Precision at 0.5 and 0.95 respectively. The performance of the model was evaluated in all the stages and the process was documented, test inference was done to view the model performance with a real dataset, a semi-supervised framework was used to annotate a video- based dataset. The results obtained from this assessment showcased the potential of the model in facilitating a system that could significantly enhance accessibility and independence for visually impaired people who interact with vending machines. The positive outcomes indicated that the model had the ability to successfully identify and track products within the vending machines, thus enabling users to navigate the purchasing process more effectively. The model demonstrated promising performance and exhibited potential for integration into a larger system aimed at improving accessibility and independence for visually impaired people when interacting with vending machines. Future work includes the development of an interface.

Chapter 7

Evaluation of LSTM based models for the estimation of gait parameters in visually impaired people

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Abstract

The increasing prevalence of people with visual impairment highlights the need for assistive technologies to enhance the mobility of people with visual disabilities. This research focuses on the potential of deep learning algorithms, specifically hybrid models LSTM+CNN and LSTM+FCN, to predict essential gait parameters such as velocity, step length, distance, and step count. Using a database provided by a previous study, which includes data obtained from inertial sensors and covers nine participants in various walking conditions, these models identify temporal patterns and spatial characteristics. Predictions were compared between the hybrid models and the biomechanical model that used two sensors configurations. Seq2seq and Seq2One approaches were also tested to obtain more accurate distance measurements, when compared to the biomechanical model, it managed to outperform it in terms of prediction; however, it achieved better results compared to the LSTM+FCN model. LSTM-based algorithms can provide more precise predictions of gait parameters compared to the traditional biomechanics method; however, additional tests should be conducted for parameters like distance and step count.

Keywords: Gait analysis, deep learning LSTM, O, visual impairment

7.1 Introduction

According to the World Health Organization, globally, over 2.2 billion people face vision impairments, with significant prevalence in Latin America and Honduras [287][288][289] This study aims to address the mobility challenges faced by visually impaired people (VIP) by developing and evaluating LSTM (Long Short Term Memory) based algorithms to accurately predict key gait parameters such as walk velocity and stride length, which are often altered in VIPs due to their reliance on non-visual navigation methods. In gait analysis, biomechanical analysis instrumentation techniques, such as spatiotemporal parameter analysis systems, are used to obtain quantitative and objective data. The systems used in the prediction of spatio-temporal parameters provide benefits such as the development of a biomechanical model of gait, generate better precision and accuracy in real time, in addition, are easily implemented in user assistance devices for training in orientation and mobility [149]. Estimating gait parameters in VIP people is a fundamental process in understanding and improving mobility in this population during rehabilitation phases, but also in the context of developing assistive technology for navigation. People with visual impairment generates a navigation route to locate themselves, therefore in rehabilitation the Orientation and Mobility (O) specialists teach them how to carry out this navigation route using auditory perception in order to pick up a wide range of sounds in different directions [290]. Traditional methods for estimating gait parameters in VIP often rely on manual measurements or subjective observations, which can introduce variability and potential measurement errors. Traditional methods for modeling human movement often need complex setups involving 3D motion tracking and detailed anatomical models [291]. One approach involves direct estimation using biomechanical models or kinematic chains [292]. This research introduces a novel approach by integrating data from inertial sensors in combination with advanced deep learning algorithms to enhance the precision of gait parameter predictions in VIP [293]. Inertial sensors offer an innovative way to collect accurate motion data with minimal invasion [294] [130]. In a previous study using Inertial Measurment Unit sensors (IMUs), two methods were tested to estimate the step length, gait velocity, step count, and total displacement in people with visual impairments. These two methods were the two-sensor configuration (TWS), and single-sensor configuration called thigh sensor (THS)[290]. In order to present a deep learning method using the collected data from this previous study, we employed LSTM based networks, known for their effectiveness in sequence prediction [295], alongside Convolutional Neural Networks (CNNs), which are a useful tool in time series prediction of human movement [296] [299], and Fully Convolutional Networks (FCNs) [293], which excel in processing spatial data [11]. This research compares TWS and THS estimations with hybrid CNN+LSTM and LSTM+FCN neural network models estimations. These technologies are integrated to develop models that improve the detection and analysis of gait parameters, a key aspect in improving mobility for visually impaired people.

Table 7.1: Table5.1 Walking tasks for acquisition

	Distance	Instructions
1	7-10 meters	Normal velocity from point A to point B
2	7-10 meters	Fast velocity from point A to point B
3	7-10 meters	Slow velocity with short strides from point A to point B
4	14-20 meters	Normal velocity with two stops in a hallway from point A to point B
5	60-100 meters	Normal velocity outdoors from point A to point B

7.2 Materials and Methods

7.2.1 Experimental Setup and Data Collection

To assess the effectiveness of LSTM-based algorithms for estimating gait parameters in VIP, the experimental setup was adapted from the methodology used in the study [290]. This previous study recruited nine visually impaired, aged 23-70, to perform walking tasks in familiar environments (home). The tasks varied in conditions and velocities as detailed in Table 5.1

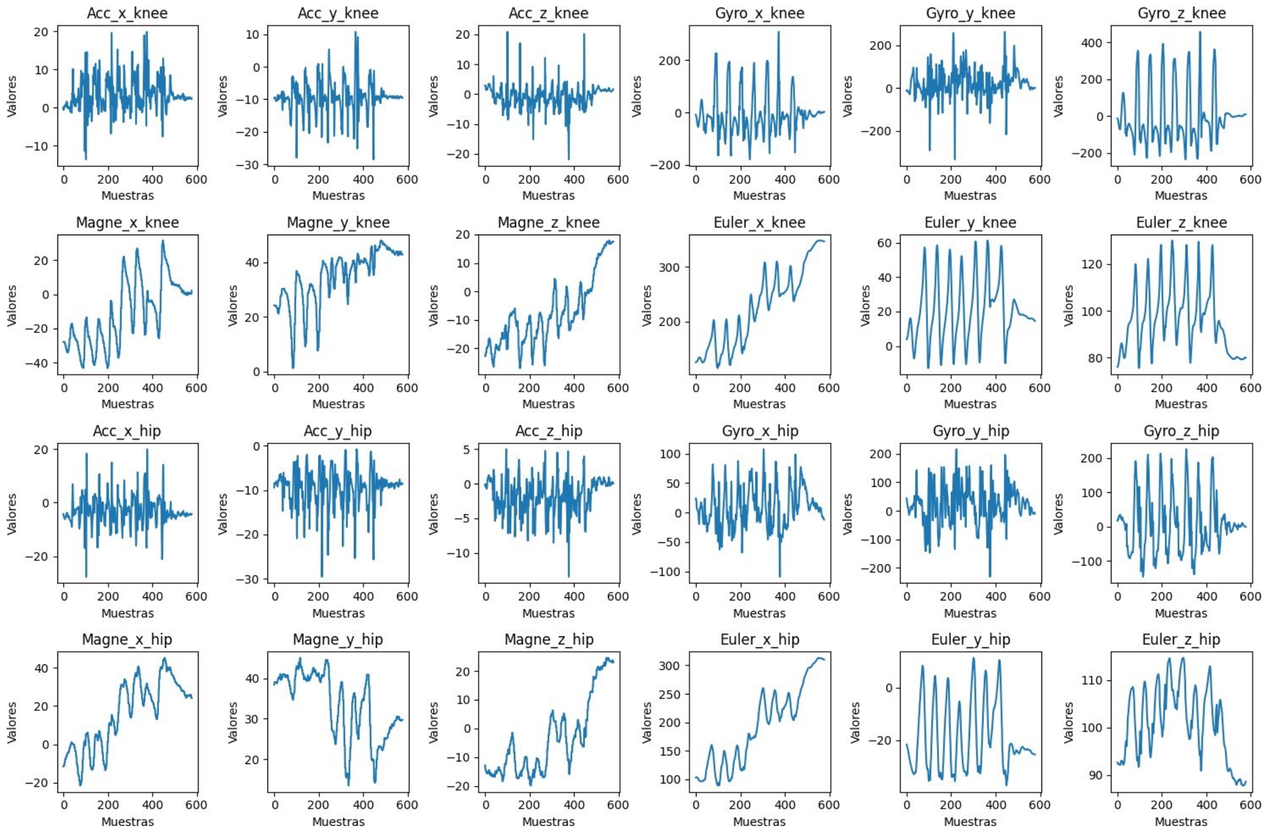

Figure 7.1: Input signal sample from Subject 8

7.2.2 Data Processing

Video recordings obtained in [290] were used for data verification as well as reference for filtering and validating the collected data, with raw data cross-referenced for accuracy. Fig 1. shows a sample of the acquired signals in one walking task, used as input for the trainings. Ground truth values for gait parameter estimation, the walked distance and step count of each participant in different experimental conditions were manually measured based on the video recordings. The key data used in this research included 1494 steps and 732 meters traveled, with average step length of 0.5 ± 0.11 meters and a velocity of 0.73 ± 0.3 m/s.

7.2.3 LSTM-based Models

Following [293], two main models were tested: 1) 4FCN+LSTM Model: For the 4FCN+LSTM model, the data underwent preprocessing, including standardization using Min-Max scaling. The dataset was divided into training and testing sets. The training process was conducted using the training set, and model performance was evaluated on the test set. The input data for the 4FCN+LSTM model is a windowed sequence of sensor measurements collected from wearable sensors attached to visually impaired volunteers. Each sequence contains a fixed number of time steps (window size) [**?**] and includes multiple features such as accelerometer, gyroscope, magnetometer and orientation values of readings from leg locations. The output of the 4FCN+LSTM model is a sequence of values representing the estimated gait parameter. The model is trained to predict this continuous value based on the input sequences of sensor measurements. 2) CNN+LSTM Model: Similar preprocessing steps were applied to the CNN+LSTM model. Training and validation were performed, and model convergence was analyzed through loss plots. The input data and output of this model are similar to the one of the 4FCN+LSTM model. In both models, the goal is to learn the relationships between the input sensor data and the gait parameter (step length, velocity, distance and step count) through training. The models use various layers, such as LSTM, Conv1D, and dense layers, to capture temporal patterns and spatial features in the input data. The resulting output provides an estimation of the gait parameter for visually impaired based on their movement data collected by wearable sensors. Fig 5.2 shows the different characteristics of both models.

Parameters		LSTM+4FCN	CNN+LSTM
Layers with neurons		3 Dense Layers: (32 neurons, 16 neurons, 8 neurons)	2 Dense layers (100 neurons, 1 neuron)
		Regressor Layer: 1 neuron	
Dropout rate		0.5	0.5
Activation function		LSTM Layer (First): default (tanh)	2 TimeDistributed Conv1D Layers: ReLU
		3 Dense layers: ReLU (Rectified Linear Unit)	LSTM Layer: Default (tanh)
		Regressor Layer: ReLU (output is non-negative)	2 Dense layers: ReLU
			Output layer: Linear
Optimizer		RMSprop	Adam
Loss function		Mean Squared Error (MSE)	Mean Squared Error (MSE)
Batch Size	Test 1	128	128
	Test 2	256	256
	Test 3	128	128
Epochs	Test 1	25	25
	Test 2	25	25
	Test 3	30	30

Figure 7.2: Model Characteristics

Both models use different layer architectures to process the input sequences and extract relevant features. Dropout is used to prevent overfitting by randomly disabling some neurons during training. The ReLU activation function introduces non- linearity, while the Linear activation function in the output layer produces continuous predictions. The optimizer, RMSprop, adapts learning rates for efficient weight updates. The number of epochs determines the number of times the model iterates over the training data, and batch size controls the number of samples used in each weight update step. Fig.3 shows the Model architecture of the two different models.

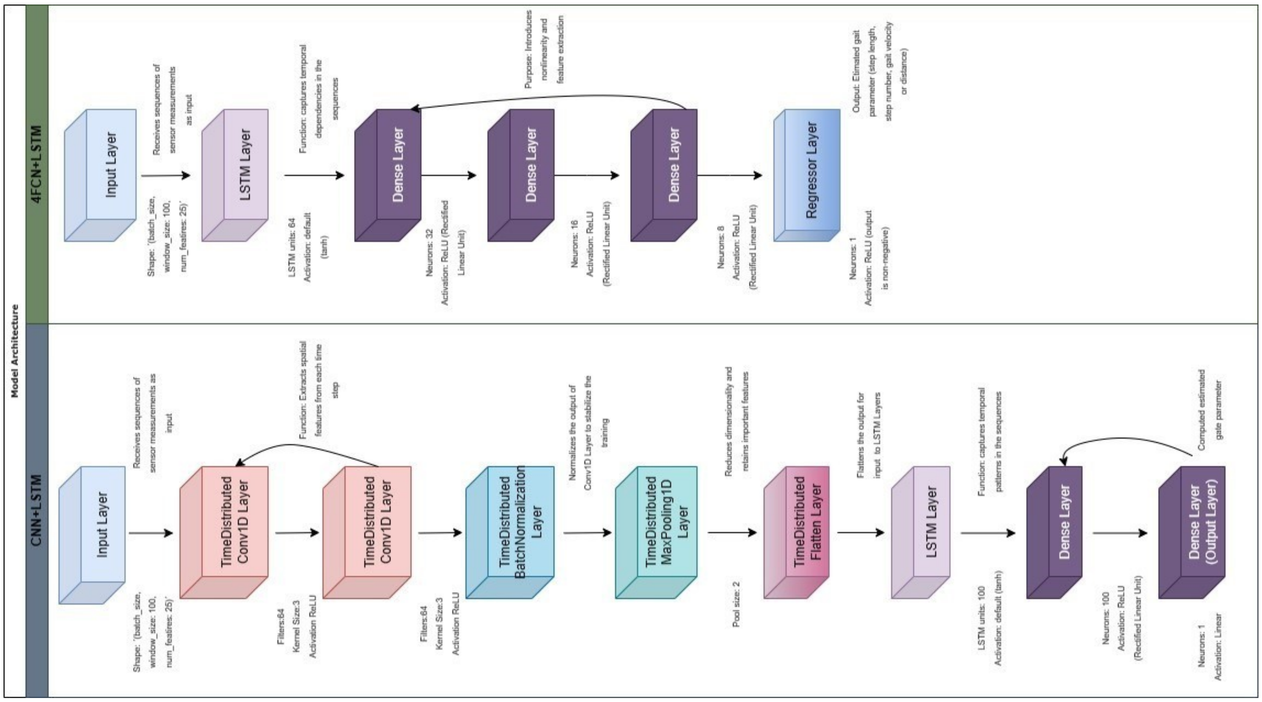

Figure 7.3: LSTM-based Models Architecture

3) LSTM+FCN Algorithm Alternative - Sequence-To-One: The Sequence-to-One prediction model was adopted because of its ability to condense a sequence of input data into a single prediction. This approach is especially useful when one wants to summarize temporal information into a single output, which can be essential for applications where rapid decision making is sought or when the focus is on forecasting a specific point in time [298]. In this case, it was used for the prediction of step counter and distance parameters. Data preprocessing for the Sequence-to-One model is important. Here, the time series is transformed into multiple samples where each sample contains a sequence of input data that correlates to a single output. This transformation allows the model to learn from a wide variety of time sequences and predict a specific output based on them. The correct structuring of this data is crucial to the success of the model, as it determines how the model will interpret and use the temporal information. Whereas the previous approach (Sequence to sequence) takes one sequence of data and predicts another sequence, Sequence-to-One takes one sequence and predicts a single piece of data. This fundamental difference alters the design and architecture of the model, as well as its application.

7.3 Results

This research evaluates the efficacy of FCN+LSTM and CNN+LSTM models in predicting stride length, step count, distance, and velocity for visually impaired, focusing in identifying the most effective model for gait parameter estimation, contributing to improved assistive technologies for visual impairment. In the study, nine visually impaired subjects participated, resulting in a total of 35 experiments used for this research, leading to a total of 210 predictions being made for each gait parameter. Specifically, 105 predictions were made for each of the two models used: FCN+LSTM and CNN+LSTM. Additionally, for the FCN+LSTM model (Sequence to One), 70 predictions were made between the step count and distance parameters.

Table 5.II compares the performance of the FCN+LSTM and CNN+LSTM models in estimating stride length. The results indicate that the FCN+LSTM model consistently demonstrates superior accuracy with lower error margins across multiple tests with a 0.015 average MAE, which is lower compared to the CNN+LSTM model and the previous research conducted by [290].

Table 7.2: Results error metrics for the stride length measurements / AVERAGE REGRESSION METRICS (METERS)

Model		Test		
LSTM + CNN		Test 1	Test 2	Test 3
	RMSE	0.0683 ±0.0941	0.1135 ±0.1302	0.0911 ±0.0928
	MAE	0.0549 ±0.0916	0.0755 ±0.1325	0.0574 ±0.0870
LSTM + FCN		Test 1	Test 2	Test 3
	RMSE	0.0247 ±0.1183	0.0380 ±0.0992	0.0204 ±0.0644
	MAE	0.0300 ±0.0208	0.0282 ±0.0725	0.0157 ±0.0447

The data in Table 5.III illustrates that both LSTM models achieved lower Mean Absolute Error (MAE) values compared to the biomechanical model in [290], indicating their enhanced accuracy in velocity estimation. Specifically, the FCN+LSTM model exhibited a notably lower average MAE of 0.018 suggesting its superior performance in predicting stride velocity with greater precision.

Tables 5.IV and 5.V present outcomes for distance and step count predictions using the FCN+LSTM model with the Sequence to One approach. The results indicate that this model achieved better accuracy in distance measurement, as shown by lower error metrics compared to other models. However, there was higher variability in step count prediction. Since previous studies [298] shows better results in the matter and noting a smaller MAE experiments 1-4 with an average of 4.21 compared to the 16.06 as the overall average, there should be better results if we increased the amount of data.

Table 7.3: Results error metrics for the velocity measurements /AVERAGE REGRESSION METRICS (METERS PER SECOND)

Model		Test		
LSTM + CNN		Test 1	Test 2	Test 3
	RMSE	0.0675 ±0.0499	0.0901 ±0.0862	0.0990 ±0.0917
	MAE	0.0442 ±0.0501	0.0744 ±0.0886	0.0864 ±0.0793
LSTM + FCN		Test 1	Test 2	Test 3
	RMSE	0.0325 ±0.1735	0.0420 ±0.1221	0.0280 ±0.0543
	MAE	0.0181 ±0.0372	0.0282 ±0.0826	0.0181 ±0.0390

Table 7.4: DISTANCE ERROR METRICS WITH THE SEQUENCE TO SEQUENCE AND SEQUENCE TO ONE APPROACH

Model		Type	
LSTM + FCN		Seq2seq	Seq2One
	RMSE	16.6168 ± 8.9523	2.9598 ± 3.3102
	MAE	13.1285 ± 7.9345	2.9598 ± 3.3102

Table 7.5: STEP COUNT ERRROR METRICS WITH THE SEQUENCE TO ONE APPROACH

Model		Type
LSTM + FCN		Seq2One
	RMSE	16.0566 ± 4.2095
	MAE	16.0566 ± 4.2095

7.4 Conclusions

The results of this study showed that Deep Learning is more effective than the traditional method in predicting gait parameters for VIP. Deep Learning, particularly LSTM+FCN models, showed higher accuracy in predicting stride length and velocity, outperforming traditional methods with lower prediction errors. Data preprocessing techniques, such as sequence-to- sequence and sequence-to-one approaches, significantly influ enced prediction accuracy. The Sequence-to-Sequence model may be more useful to predict complete time series; such as patterns of behavior over time. The Sequence-to-One, on the other hand, is more suitable for situations where the interest is focused on forecasting a specific event or a specific piece of data based on a sequence of prior information such as distance traveled and total number of steps. The study successfully demonstrates the potential of LSTM- based models, particularly FCN+LSTM and CNN+LSTM, in enhancing gait analysis for visually impaired people. The FCN+LSTM model accurately predicted stride length and velocity, with some variability in step count and distance measurements. These findings highlight the significant implications for developing more efficient and accurate assistive technologies, potentially leading to improved mobility and independence for visually impaired.

Chapter 8

General Discussion

8.1 Challenges Solutions

IMU sensors have been used in this research as principal component in assistive technologies for visually impaired people during rehabilitation, and the challenges faced are similar to those challenges faced in the literature where IMU sensors are used for navigation, guidance, and full-body motion tracking.

- The first challenge is accuracy: IMU sensors can be influenced by various types of errors, which can impact their accuracy and reliability leading to inaccurate measurements over time.

  Bias: This is a constant error that affects the accuracy of the sensor readings. It can be due to factors such as manufacturing imperfections, temperature variations, or aging of the sensor components.

  Noise: IMU sensors can be affected by random noise, which can introduce fluctuations in the sensor measurements. This can be due to factors such as electronic interference, mechanical vibrations, or environmental conditions[274].

  Scale factor error: This type of error can cause the sensor to over- or under-report the measured quantities. It can be due to factors such as non-uniformity in the sensor's response or variations in the sensor's characteristics over time.

  Misalignment: This error occurs when the sensor axes are not perfectly aligned with the reference frame. It can lead to inaccuracies in the measured quantities, especially when the sensor is used in complex motion scenarios.

  Drift: Drift is a gradual change in the sensor readings over time, even in the absence of any motion or external influences. It can be due to factors such as sensor aging, temperature variations, or mechanical stress[275].

Understanding and mitigating these errors is crucial for improving the accuracy and reliability of IMU sensors, especially in applications such as inertial navigation and motion tracking. Advanced calibration, signal processing, and error modeling techniques are often used to address these challenges and enhance the performance of IMU-based systems. In the studies proposed in chapters 4 and 5 in order to mitigate the errors related to precision, we have chosen to use biomechanical references that serve as parameters to reduce the errors of the sensors. Subsequently deep learning models for accurate predictions are proposed in chapter 7. It can be clearly observed as part of the results and discussion in sections 4.3 and 5.3 (Results), and 4.4 and 5.4 (Discussion) how the use of the biomechanical model as a reference has the potential to significantly reduce these errors.

- The second challenge is the complexity of sensor fusion: Integrating data from multiple sensors, such as accelerometers, gyroscopes, and magnetometers, to improve accuracy can be complex and computationally intensive.

  The complexity of processing data from multiple sensors in the fusion algorithm, such as accelerometers, gyroscopes, and magnetometers, can vary. While the fusion of data from different sensors can be computationally intensive, the complexity of processing data from those sensors in the fusion algorithm is relatively low for some sensor combinations. For example, in an IMU and GPS fusion algorithm, the complexity of processing data from accelerometers and gyroscopes is relatively low compared to the complexity associated with processing data from GPS, in some cases, the magnetometer, which runs at relatively low sample rates [276]. Sensor fusion algorithms play a crucial role in the sensor fusion process, as they determine how the data from various sensors are weighted, processed, and integrated. One of the primary challenges associated with sensor fusion is the computational complexity involved in processing and integrating data from multiple sensors. As the number of sensors and the volume of data increases, the processing power and memory requirements for fusing this data also grow, which can lead to increased latency and reduced real-time performance, especially in critical applications such as autonomous vehicles or robotics [277].

  To address the computational complexity of sensor fusion, we have also used the body reference points from biomechanical models, as other authors may suggested [278]. Using fixed-point arithmetic, and orientation angles from sensor fusion can significantly decrease the computational complexity while maintaining high fusion quality, making the algorithms applicable for applications with human interaction

  IMU sensors alone may not provide sufficient information for navigation in complex environments, such as indoors or in crowded spaces. Researchers currently explores the use of multiple sensors for environmental context detection and navigation, as explained in Chapter 3.4 (Discussion), section 3 "Field of Applications" . For instance, environmental context detection for navigation may be based on multiple sensors that combine not just IMU sensors, but other, such as cameras, lidar, or ultrasonic sensors. This can improve the accuracy and reliability of navigation in complex environments [279]. Also, IMU sensors can be combined with other sensors, such as magnetic tensor sensors, infrared sensors, and GPS, for indoor and outdoor navigation applications for visually impaired people [280]. The use of multiple sensors for navigation and environmental context detection can provide more comprehensive and accurate information about the environment, which can improve the performance of assistive technologies for visually impaired people. This could be a future line of study while developing specific rehabilitation programs and scenarios for the visually impaired, since orientation and mobility rehabilitation exercises should ideally be developed in familiar environments such as their homes and workplaces. However, this leads to the great challenge that the flexibility of these sensing environments can be very different for each person undergoing rehabilitation. That is why we propose to focus on the sensing of the persons movement executing mobility techniques, which should be, if well executed, safe enough, and sufficient to navigate any unfamiliar environment.

Integrating data from multiple sensors can be complex and computationally intensive, requiring advanced signal processing and fusion algorithms [279][281]. Therefore, ongoing research is needed to develop efficient and effective sensor fusion techniques that can handle the complexity of multiple sensor data and provide reliable and accurate information for navigation in complex environments [279].

As shown in Chapter 3; IMU sensors often need to be combined with other technologies, to provide accurate and reliable environmental information, however is proven by this thesis that this sensors can perfectly represent the biomechanical model of gait that is being executed. The fusion of data from different sensor types, such as cameras, LIDAR, ultrasonic sensors, and IMUs, allows for enhanced accuracy in decision-making and overall system performance, if applicable [282]. In the context of assistive technologies for visually impaired people, the literature widely presents the combination of IMU sensors with other sensors such as GPS, compass, beacons, RGB-D cameras, and ultrasonic sensors has been explored to improve navigation accuracy in various environments, including indoor and outdoor settings [282][283]. However, the integration of data from multiple sensors can be complex and computationally intensive, posing challenges in real-time performance, especially in critical applications such as autonomous vehicles or robotics [277]. Advanced sensor fusion algorithms are crucial in combining data from multiple sensors effectively, and they play an important role in reducing errors and noise in the collected data, leading to enhanced accuracy in decision-making and overall system performance [277].Therefore, ongoing research is needed to develop efficient and effective sensor fusion techniques that can handle the complexity of multiple sensor data and provide reliable and accurate information for navigation in complex environments [284].

This thesis also focused on developing a specific solution for a specific user, a wearable capable to serve as hardware of an assistive technology rehabilitation system (Chapter 10). This, with the purpose of facing the challenges related to the size, weight, and power consumption of IMU sensors, that as mentioned in the literatura can be limiting factors for wearable assistive devices [279].

8.2 Results analysis and solution integration

8.2.1 Inertial Measurement Unit Sensors in Assistive Technologies for Visually Impaired People, a Review

The review of IMU sensors in assistive technologies for visually impaired people has revealed several key findings and specific insights. IMU sensors have been successfully integrated into navigation systems, obstacle detection systems, and rehabilitation aids, offering distinct advantages such as low cost, small size, and the ability to function reliably in various environments. However, challenges remain, including sensor noise, drift, and the need for calibration, which can impact accuracy and usability. The review emphasizes the need for future research to focus on the development of more robust and accurate IMU technologies, implementation of user-centered design, and exploration of new applications for IMU sensors in assistive technologies, such as real-time feedback systems for gait, posture, and environmental interaction. User-centered design is highlighted as a crucial but often overlooked aspect, and the review calls for more exploration of rehabilitation and biomechanical analysis applications for IMU sensors to expand their benefits for VIP. Overall, the review suggests that IMU sensors hold considerable promise for improving mobility and independence for VIP, but technological advancements and a focus on user-centered design are paramount for maximizing their potential and ensuring they effectively address the needs of VIP. Specific insights from the Review's results are highlighted as follows:

- IMU sensor fusion with other technologies often yields optimal outcomes.
- IMU sensors hold considerable promise for improving mobility and independence for VIP.
- User-centered design is a crucial but often overlooked aspect, future research should prioritize understanding VIP needs and preferences to create truly accessible and user-friendly assistive technologies.
- Rehabilitation and biomechanical analysis applications for IMU sensors are largely untapped: The review calls for more exploration in these areas to expand the benefits of IMU technology for VIP.
- Technological advancements and a focus on user-centered design are paramount for maximizing the potential of IMU-based assistive technologies and ensuring they effectively address the needs of VIP.

Based on the results, the proposal of a motion measurement system to support visually impaired people in rehabilitation using low-cost inertial sensors aligns with the key findings and specific insights from the review of IMU sensors in assistive technologies for VIP. The review highlights the considerable promise of IMU sensors for improving mobility and independence for VIP, as well as the need for user-centered design and more exploration of rehabilitation and biomechanical analysis applications for IMU sensors. The proposed motion measurement system using low-cost inertial sensors can address the need for more exploration in rehabilitation and biomechanical analysis applications. The system aims to provide motion analysis of the long cane and the leg, offering quantitative parameters for O&M

training. This aligns with the call for more exploration in rehabilitation and biomechanical analysis applications for IMU sensors to expand their benefits for VIP. Additionally, the review emphasizes the importance of user-centered design and understanding VIP needs and preferences to create truly accessible and user-friendly assistive technologies. The proposed system, by providing quantitative parameters that are currently visually analyzed during rehabilitation, can contribute to a more user-centered approach by addressing the limitations of human, technological, and structural resources in some regions, especially those with economic constraints. In summary, the proposed motion measurement system using low-cost inertial sensors aligns with the key findings and specific insights from the review, and it has the potential to contribute to the advancement of IMU-based assistive technologies for VIP by addressing the identified research priorities and needs

8.2.2 A Proposal of a Motion Measurement System to Support Visually Impaired People

The proposal of a motion measurement system to support VIP in rehabilitation using low-cost inertial sensors aligns with the key findings and challenges identified in the review of IMU sensors in assistive technologies for VIP. The proposed system aims to effectively track the motion of the long cane and the leg of VIPs during rehabilitation, providing quantitative parameters for orientation and mobility training. The system has been found to reliably measure grip rotation, safety zone, sweeping amplitude, and hand position with an accuracy of around 97.62%. However, the accuracy of step length measurement is lower at 94.62%, indicating the need for further development in this area. The challenges identified in the review, such as improving the accuracy of step length measurement and developing a user-friendly interface for the system, are consistent with the areas that the proposed system needs to address. Additionally, the future directions outlined in the review, including addressing the identified challenges, investigating the use of the system in other applications, and conducting longitudinal studies to assess its long-term effectiveness, are relevant to the proposed motion measurement system. In summary, the proposed motion measurement system using low-cost inertial sensors aligns with the key findings and challenges identified in the review, and it has the potential to address the current limitations and improve the practice of O&M training for VIPs. However, further development, testing, and research are needed to fully realize its potential.

Specific key findings are highlighted as follows:

- A low-cost motion measurement system using inertial sensors can effectively track the motion of the long cane and the leg of visually impaired people during rehabilitation.
- The system can reliably measure grip rotation, safety zone, sweeping amplitude, and hand position with an accuracy of around 97.62
- The accuracy of step length measurement is lower at 94.62

Overall, the system has the potential to improve the current practice of orientation and mobility training for VIP, however, there are clear challenges found. A need to improve the accuracy of step length measurement. The need for developing a user-friendly interface for the system. Conducting further testing of the system in real-world settings.

The findings from the proposed method of a low-cost motion measurement system using inertial sensors for VIP in rehabilitation, as well as the challenges and future directions, led to advances in the research and a new paper, The new paper aims to further explore the use of wearable sensors, specifically in estimating spatiotemporal parameters of gait and posture for VIP. The findings from the review and the low-cost method have provided a foundation for the new paper by highlighting the potential of low-cost motion measurement systems using inertial sensors to improve O&M training for VIP, while also identifying areas for further development and research. The new paper seeks to build upon the existing knowledge and address some of the challenges identified in the review, such as improving the accuracy of step length measurement and developing a user-friendly interface for the system. By focusing on the estimation of spatio-temporal parameters of gait and posture, the new paper aims to contribute to the ongoing research in the field of assistive technologies for VIP. The findings from the review have provided valuable insights that have informed the direction of the new paper, and the two works are complementary in their efforts to advance the use of inertial sensors in rehabilitation and O&M training for VI

8.2.3 Estimation of Spatio-Temporal Parameters of Gait and Posture of Visually Impaired People

Wearable inertial sensors can be used to accurately estimate spatio-temporal parameters of gait and posture of visually impaired people. The study proposed a simple architecture using two low-cost inertial sensors placed on the lower back and the upper leg. The parameters were calculated using absolute orientation angles, and two different sensing architectures were tested for gait according to a selected biomechanical model. A simple architecture using two low-cost inertial sensors placed on the lower back and the upper leg was found to be effective in estimating distance traveled, step detection, gait velocity, step length, and postural stability. The proposed method showed good agreement with ground truth data for all parameters, with mean absolute errors of less than 10The results suggest that the proposed method could be used as a tool for assistive technology designed for orientation and mobility training to assess gait parameters and/or navigation.

In summary of the findings, there is still identified the need to improve the accuracy of step length measurement, which was the least accurate parameter measured in the study. Developing a more robust algorithm that is less sensitive to sensor noise and drift was also highlighted as a challenge. It was clear that is needed to conduct further testing of the proposed method in different walking conditions and with a larger sample of VIPs.

There were several limitations in the study, as mentioned as follows:

- The proposed method was tested in several walking conditions, however, it is necessary to test it in different walking conditions, such as walking on uneven surfaces or walking up and down stairs.
- The proposed method should also be tested with a wider range of VIPs, such as VIPs with different levels of visual impairment or VIPs with different gait patterns, the VIPs

volunteers were a small group.

- The study did not investigate the long-term effectiveness of the proposed method in improving the mobility and independence of VIPs.

With the identified challenges and limitations, The findings from the study led to more testing with the gathered data, In Chapter 7.2.5 the evaluation of deep learning LSTM Algorithms for the improvement of the Estimation of Gait Parameters in Visually Impaired People is presented as a final stage of the doctoral thesis. These final steps are not published yet as a paper, and not presented in the article compendium. However, is added to this section as it aims to further explore the estimation of gait parameters in VIP using the same gathered data with the visually impaired volunteers. This indicates that the findings from the original study have sparked further research and interest in the use of wearable inertial sensors for estimating gait parameters in VIP.

8.2.4 Computer Vision-Based Assistance System for Visually Impaired Individuals in Vending Machine Interactions

As mentioned before, one of the most important steps to developing assistive technology for visually impaired people, which is a current challenge in literature, is developing a user-friendly interface for the system. Computer vision technology has the potential to increase accessibility for the visually impaired. Research in assistive technology for visually impaired people has resulted in some very useful hardware and software tools in widespread use, such as text magnifiers, screen readers, Braille note-takers, and document scanners with optical character recognition. However, very few computer vision systems and algorithms are currently employed to aid visually impaired people. A promising research direction is the use of computer vision to detect natural or artificial landmarks, and thus assist in blind wayfinding. A VI can use their cell phone, the camera pointing forward, to search for landmarks in view. Natural landmarks are distinctive environmental features that can be detected robustly and used for guidance either using an existing map or by matching against possibly geotagged image data sets.

The final paper presented in the thesis of the compendium of articles is in the same integrating solution because it addresses the common goal of leveraging technology to improve the lives of VIP. While the specific focus of the paper is on assisting VIP in vending machine interactions, it aligns with the broader theme of developing assistive technology using computer vision for the visually impaired. The paper contributes to the ongoing research and development of user-friendly computer vision-based systems to enhance the accessibility and independence of VIP in various aspects of daily life. The integration of research on computer vision-based assistance systems for the visually impaired, including the use of natural or artificial landmarks and the development of user-friendly interfaces, reflects a holistic approach to addressing the diverse needs of the visually impaired community. By leveraging technology and innovative solutions, researchers and developers aim to create practical and effective assistive technology that empowers VIP and enhances their quality of life. The paper presents a study that aimed to develop a computer vision-based system to facilitate interactions with vending machines for VIP. The study involved the creation of a custom dataset of images, the training of several models using YOLOv5 notebook, and the evaluation of the model's performance. The final model achieved a precision of 89%, recall of 85%, and mean average precision of 88% and 78% at 0.5 and 0.95 thresholds, respectively. The model's performance was evaluated at all stages, and test inference was conducted to assess its performance with real datasets. The study also used a semi-supervised framework to annotate a video-based dataset. The results indicated that the model had the potential to significantly enhance accessibility and independence for VIP interacting with vending machines. The model demonstrated promising performance in identifying and tracking products within vending machines, thereby enabling users to navigate the purchasing process more effectively. The study suggested that the model could be integrated into a larger system aimed at improving accessibility and independence for VIP when interacting with vending machines. The future work includes the development of a user-friendly interface for the system. The findings from the paper align with the broader research in assistive technology for VIP, which has resulted in the development of various hardware and software tools. However, the use of computer vision systems and algorithms to support them in their daily tasks is still limited. The paper highlights the potential of computer vision technology to detect natural or artificial landmarks and assist in blind wayfinding, which can significantly enhance the independence and accessibility of VIP. The positive outcomes of the study demonstrate the potential of the developed computer vision-based system to improve the interaction of VIP with vending machines, thereby contributing to the broader goal of enhancing accessibility and independence for this population.

The paper's findings contribute to the ongoing research and development of computer vision-based assistive technology for VIP, and the development of a user-friendly interface for the system is identified as a key area for future work. The integration of computer vision technology into assistive systems has the potential to significantly improve the lives of VIP by enhancing their independence and accessibility in various daily tasks and interactions.

8.2.5 Evaluation of LSTM-based algorithms for the estimation of gait parameters

The use of inertial sensors and machine learning algorithms, such as LSTM-based algorithms, has emerged as a possible solution to accurately predict gait parameters in blind people. Recent advances in inertial sensor technologies and machine learning have allowed for more effective approaches to predicting gait parameters in blind people. The combination of these advances has led to the emergence of LSTM-based algorithms as a promising tool for predicting gait parameters. However, there is still room for improvement in the application of prediction algorithms to improve performance and accuracy in estimating gait parameters. Specifically, predicting gait parameters in visually impaired people is a complex issue that needs to be addressed in-depth due to the complexity of gait and the variability among these people. Future research should focus on improving the accuracy and robustness of these algorithms, as well as investigating their use in other applications such as obstacle detection and gait analysis. Longitudinal studies are also needed to assess the long-term effectiveness of these algorithms in improving mobility and independence [130]

The problem lies in the accuracy of the methods used to calculate gait parameters in VIPs. Methods that use inertial sensors placed on leg segments focus on two approaches to determine gait parameters. "One approach involves the identification of related variables that are correlated with unknown parameters. Another approach involves direct estimation using biomechanical models or "kinematic chains" [285]. These traditional approaches may have limitations in capturing complex gait patterns in the gait data of these populations. This is because the walking style and gait patterns may differ in VIP. On the other hand, methods based on LSTM algorithms offer higher accuracy and adaptability in predicting gait parameters as they avoid the problem of decreasing error signals between layers by making LSTM networks "remember" information for longer periods [286]. Those two new research question arises: Can the gait parameters in visually impaired people can be predicted using LSTM algorithms and inertial sensor and, how does it compare to traditional calculation methods? To answer this questions, and to assess the effectiveness of LSTM-based algorithms for estimating gait parameters in the visually impaired, the experimental data acquired and published in the article “Estimation of Spatio-Temporal Parameters of Gait and Posture of Visually Impaired People Using Wearable Sensors” was adapted and pre-proceed as follows: The experimental sessions were video recorded, providing valuable visual information for subsequent data analysis. These video recordings were crucial for filtering and validating the collected data. The raw data, initially stored in CSV files, were cross-referenced with the video recordings to ensure accuracy and consistency. To establish ground truth values for gait parameter estimation, the walked distance and step count of each participant in different experimental conditions were manually measured based on the video recordings. These visually derived measurements served as a reference for the accuracy of the collected data. GT values served as the reference for assessing the accuracy of the estimation methods. The data used in this research contained a total of 1494 steps and 732 meters traveled. The subjects used have an average step length of 0.5 $\pm$ 0.11 meters and a velocity of 0.73 $\pm$ 0.3 m/s.

Two models were tested a 4FCN+LSTM model, which underwent preprocessing, including standardization using Min-Max scaling. The model was constructed with an input layer that accepted windowed sequences of data points and involved a series of Dense and LSTM layers. It was compiled using the RMSprop optimizer and mean squared error (MSE) loss function. The training process was conducted using the training set, and model performance was evaluated on the test set. The input data for the 4FCN+LSTM model consisted of a windowed sequence of sensor measurements collected from wearable sensors attached to visually impaired volunteers. The output was a sequence of values representing the estimated gait parameter. Similar preprocessing steps were applied to the CNN+LSTM model, and the data was divided into training and testing sets. The CNN+LSTM architecture was constructed, involving a combination of Conv1D and LSTM layers for feature extraction and sequence modeling. The model was compiled using the Adam optimizer and mean squared error (MSE) loss. Training and validation were performed, and model convergence was analyzed through loss plots. The input data for the CNN+LSTM model was also a windowed sequence of sensor measurements obtained from wearable sensors, and the output was a sequence of values representing the estimated gait parameter. The goal of both models is to learn the relationships between the input sensor data and the gait parameter (step length, velocity, distance, and step count) through training. The models use various layers, such as LSTM, Conv1D, and dense layers, to capture temporal patterns and spatial features in the input data.

The resulting output provides an estimation of the gait parameter for the visually impaired based on their movement data collected by wearable sensors. The key findings are presented in this discussion section. The results are structured around the thesis question. The findings of this study indicate that Deep Learning is more effective than the traditional method in predicting the gait parameters of people with visual impairment. The highest accuracy with the Deep Learning method was observed in stride length and velocity, with a smaller prediction error. The LSTM+FCN model achieved the most precise evaluation metrics. The method of labeling and preprocessing data also influenced prediction accuracy, as it was determined that a sequence-to-sequence approach was effective for some parameters like velocity and step length. However, further tests were needed for parameters such as distance, which had a higher error with this method. This led to a different sequence-to-one approach to evaluate this parameter along with step counting. Therefore, it was concluded that the sequence-to-one approach is suitable for predicting distance and step-counting parameters. However, despite its stability, this approach has lower adaptability and requires a larger database to achieve broader coverage and improve its prediction capacity. These results suggest that LSTM-based algorithms could be used to develop new gait rehabilitation interventions for people with visual impairment in the future.

Chapter 9

Additional Research and Data

This section highlights additional findings and developments stemming from my doctoral research. While not submitted for publication, the two main research areas presented in this section, results from years of work at the Laboratory of Bioinstrumentation and Nanomedicine's assistive technology research lines, represent advancements and contributions to the research field. Building upon the core contributions of this thesis, they offer fresh perspectives and potential for future impact.

Hardware: Open-Source, Low-Cost Inertial Sensor Device for Motion study

In the articles presented in chapters 5, 6, and 8, an Arduino-based module was utilized for data acquisition. However, numerous hardware limitations were encountered while using this module, which was originally intended solely for testing the proposed methods. Consequently, during this period, a prototype motion sensor device was also developed. The system was designed with the aim of utilizing the information of absolute orientation angles and acceleration vectors provided by the fusion of the inertial sensors comprising the inertial sensor module. This was done to assess the rotational movements of the joints performed in the coordinates where the mountable sensor is placed. Subsequently, the necessary values for the established measurements are obtained from this assessment.

The development of specialized hardware solutions for assistive technology for visually impaired users is necessary. Visually impaired people require tactile or auditory feedback and interaction. Many of the current market wearable systems developed, do not address this need. On the other hand, they aim to be small and minimally perceptible, with few additional accessories such as fingerprints. However, providing tactile information is crucial for visually impaired users.

Building on this motivation and the goal of developing assistive technology, this research leverages an understanding of user needs and technical challenges identified within the thesis. The aim is to translate these insights into a specialized inertial sensor module designed for use as a motion sensor device in assistive technology for visually impaired people.

A prototype sensor was designed with the objective of being as non-invasive and uncomplicated as possible, while still meeting the requirement of functioning as an assistive technology with both auditory and tactile feedback. Additionally, it needed to be open-source, customizable, programmable, and cost-effective. This stands in contrast to solutions currently available in the literature and on the market, which only allow for development in the programming and interface design phases, but not in hardware programming.

This hardware underwent various phases and revisions during the development of the doctoral thesis. Two final engineering degree dissertations under my supervision were integral parts of this development process:

"Performance evaluation of an embedded inertial sensor system for rehabilitation of severely visually impaired people" by Gabriela Neira, prior to obtaining the degree as Mechatronics Engineer, and "Design of a low-cost device for the study of movement in different biomedical applications" by Luis de Pablo Beltran, previous to obtaining the degree in Engineering of Telecommunication Technologies and Telecommunication.

For the first version, the design was based on recommendations from manufacturers, experts, and specialized forums. It integrated a Nordic Nrf52832 microcontroller for data processing, a Bosch BNO055 inertial sensor containing three sensors—an accelerometer, gyroscope, and magnetometer—a switch for tactile on/off functionality, a tactile button for system reset, a programmable LED, a speaker, a Bluetooth Low Energy communication antenna, and various passive components such as resistors, a 32MHz oscillator, 12 pF capacitors, and inductors. The Printed Circuit Board (PCB) design was completed using Altium schematic design software. This device featured multiple communication systems, programming accessibility, and a battery charging module (MCP723832). Schematics for the different modules comprising the device and the printed circuit board were created.

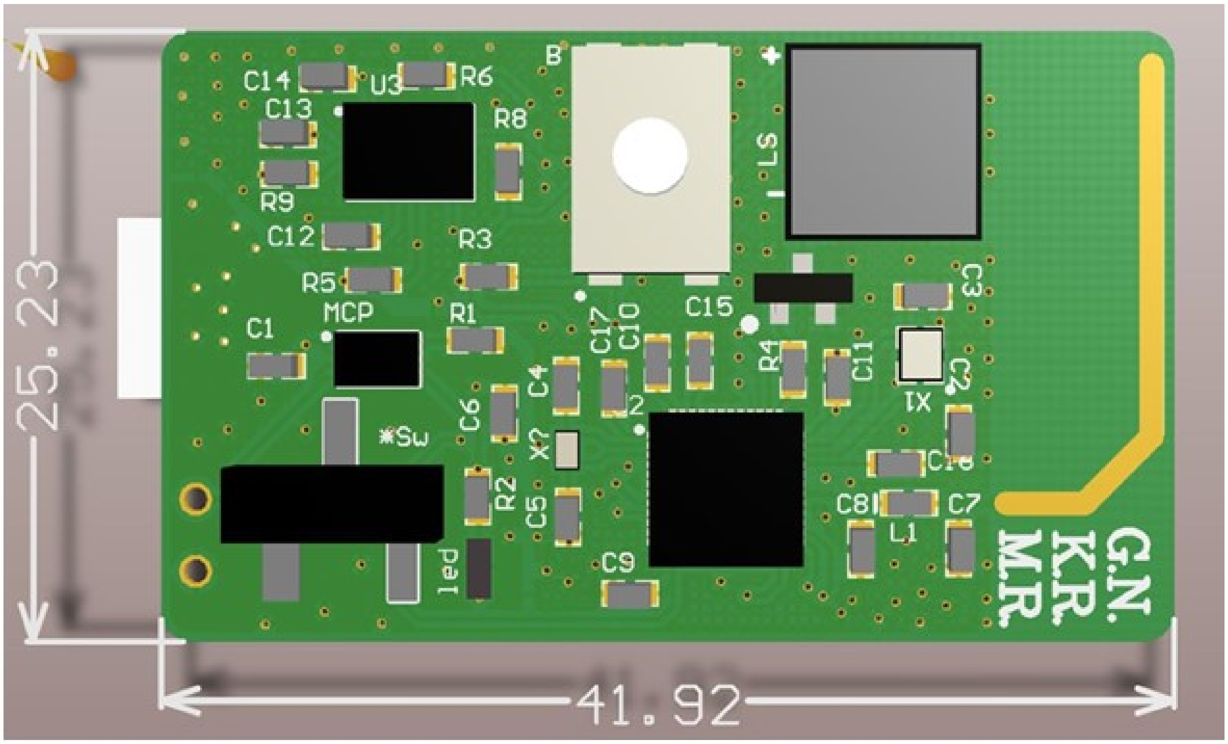

Figure 9.1: Low-Cost Inertial Sensor Device for Motion analysis First prototype.

After conducting several tests with the first prototype, a second version was proposed due to the identification of design errors and limitations. Most of the challenges were related to external communication and programming, and an electronic design problem was detected in the charge module. Consequently, a second prototype was developed. This device features a Nordic Nrf52832 microcontroller and a Bosch BNO080 inertial sensor. The choice of the inertial sensor was based on its availability in the market at that time. In this second version, UART and SPI external communication interfaces were added. Additionally, a battery charge management module, a programmable LED, a speaker, a Bluetooth Low Energy communication antenna, and several GPIOs and buttons were incorporated.

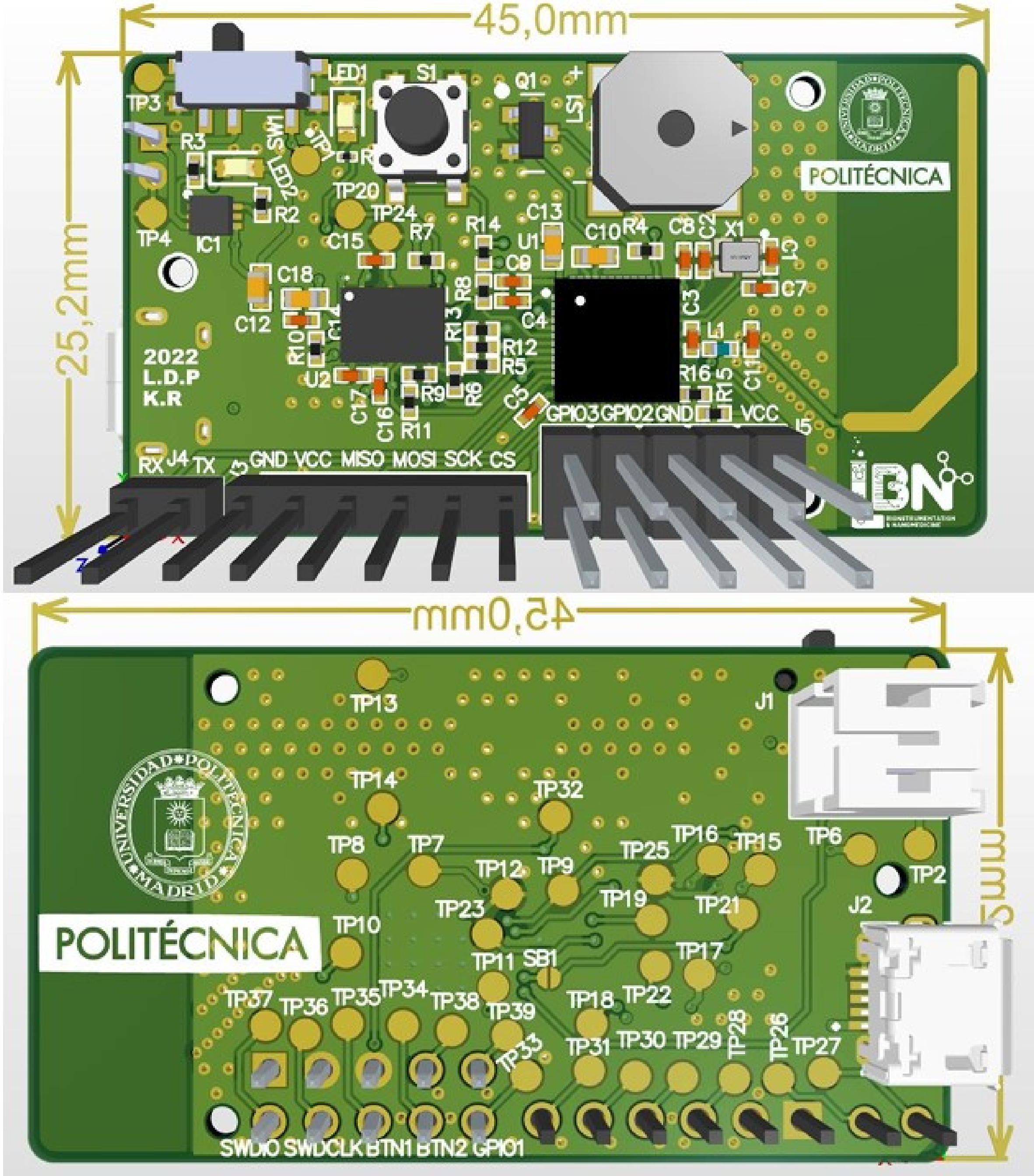

Figure 9.2: Low-Cost Inertial Sensor Device for Motion analysis Final prototype

A third and final prototype was developed based on the revision and testing of the second version. In this iteration, the only variation was the selection of the inertial sensor. Since the Bosch BNO080 was no longer available in the market, the BMM150 three axis magnetometer and BHI160 three axis accelerometer and three axis gyroscope sensors were integrated into the final version. The primary difference lies in the sensor fusion provided by the BNO055 and the

BNO080, which impacts sensor data reading for future developments. Ongoing development is currently centered on enhancing the functionality and performance of the device.

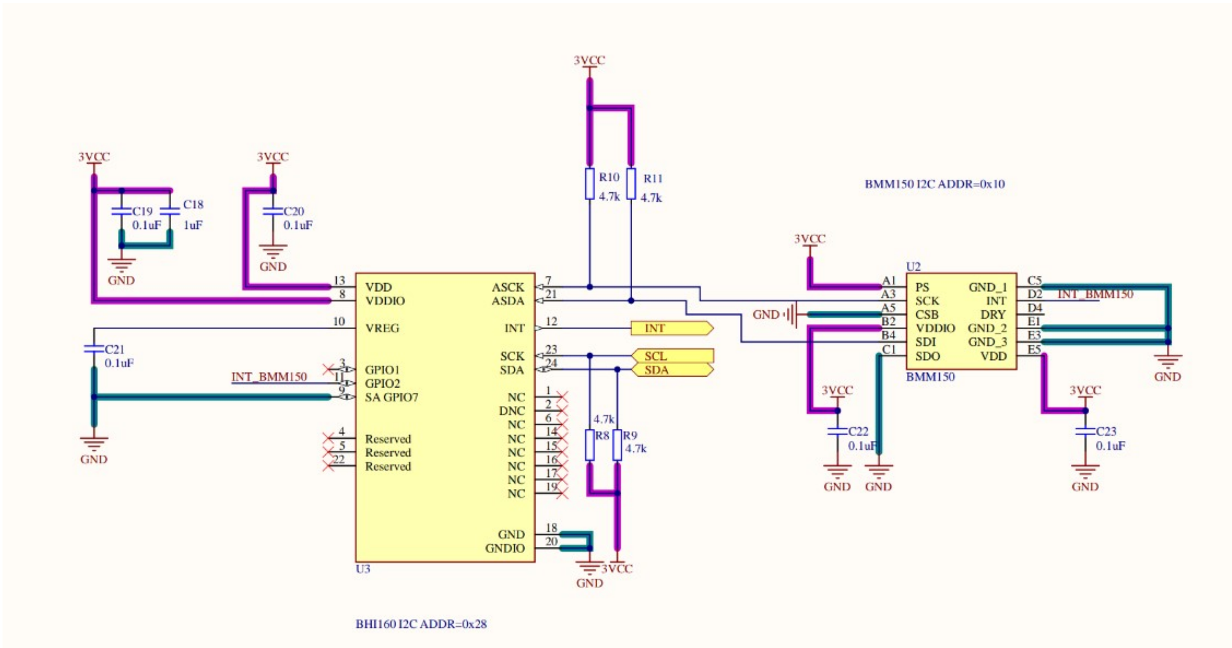

Figure 9.3: Schematic design and Pinout of the BMM150 and the BHI160

Human Computer Interaction and Interface Design for Visually Impaired users

The second research area that was developed under my supervision, focuses into the design of novel interfaces specifically catering to the needs and preferences of visually impaired people. This research leverages the knowledge gained on human-computer interaction for this population, striving to create more intuitive, efficient, and engaging interfaces.

By exploring this research line, two dissertations under my supervision was a integral part of this development process:

Development of a body posture measurement tool focused on rehabilitation of visually impaired people by Angela Suarez, previous to obtaining the degree in Engineering of Telecommunication Technologies and Telecommunication.

This project focused on addressing the challenges faced in the rehabilitation process of people with visual impairment, particularly concerning the assessment and correction of body posture. Proper posture is crucial for the effective use of tools like long canes, as well as for mastering movement techniques and performing daily activities. However, the traditional approach to posture training, which relies on in-person sessions with rehabilitation specialists, presents limitations, especially for those without access to such services. This can result in long-term complications due to uncorrected postural defects. Those, the main objective of the project was to develop a posture assessment and correction system tailored for remote rehabilitation sessions for VIP. This system incorporates an auditory feedback mechanism and is designed to accommodate the specific needs of visually impaired users. It comprises a mobile application developed in Unity using the accessibility tools and inertial sensors, in order to integrate a gamification development platform.

To achieve this goal, the project began with a thorough review of existing literature on the use of inertial sensors for posture assessment in various biomedical applications. This research supported the decision to utilize inertial sensors for the specific case of posture assessment.

The project then proceeded to conduct tests with volunteers to evaluate the effectiveness of the developed system. Many limitations regarding design of the software were encountered during the testing. However, the results of these tests indicated that the system has significant potential for enhancing the rehabilitation process of people with visual impairment. Furthermore, it was suggested that the system's applicability could extend beyond visual impairment rehabilitation to other fields such as sports training and post-operative rehabilitation.

And, **Design and implementation of a tele-rehabilitation tool for visually impaired people** by Ainhoa Blanco, prior to obtain the Master's degree in Biomedical Engineering.

This project aimed to design and implement a tool for use in the rehabilitation of VIP using integrated inertial sensors in both the cane and the patient's leg. This tool could enable the detection and recognition of sweeping techniques and gait movements performed by the patient. Specifically, it would be used by orientation and mobility specialists to remotely track the patient's progress and provide corresponding feedback. Ideally, data would be sent to the specialist in real-time.

A developed was made using Blender software to construct a virtual avatar that simulates the movements and techniques performed by the patient. Data obtained from the sensors can be uploaded to a Blender file, where they are used to animate the human avatar. Consequently, the specialist can visualize the patient's improvements without the need for an in-person rehabilitation session.

The results were positive, although there are opportunities for improvement to increase the precision of the process, real-time data acquisition was not implemented due to several limitations.

Besides this two dissertations, during the development of my doctoral thesis, I also supervised the work of 7 visiting exchange students who spent short periods in our laboratory. They also worked on software development exploring the potential of this line of work. Among which I will highlight:

Mobile application development for visually impaired people in the assistive technologies research line by Malaury Bauthier. This project explored the accessibility tools provided by android development, as well as the existing applications for visually impaired people, highlighting design opportunities for the interface and wireless communication between inertial sensors and these applications.

Development of a serious game to evaluate the performance of the rehabilitation sessions of visually impaired people by Thomas Busato.

This project focused on designing and developing a serious game specifically tailored for VIP. The game aims to facilitate a progressive approach to rehabilitation, particularly in Orientation and Mobility training, while also providing a means to evaluate the user's performance. The application is structured into multiple levels, each increasing in technique and difficulty. These levels include tasks such as properly holding the long cane (grip and rotation), walking with good posture, assessing distance by walking, and overall gait evaluation.

The application was built using Unity, a versatile platform for creating both 2D and 3D games, known for its cross-platform connectivity capabilities. It was integrated with Visual Studio and programmed using the C language. Since data acquisition involves utilizing three position sensors worn as wearable devices, the developed software needed to support the binding and transfer of raw data through BLE connection.

Research internship in electromedicine about inertial sensors for body movement monitoring by Maud Giraudeau.

This work focused on developing a system for tracking the movements of long canes within an indoor environment. The goal was to assist rehabilitation professionals in monitoring these movements, thus expediting the rehabilitation process. To achieve this, it was essential to capture data on the long cane's movements.

The recorded movement data was processed using a Python script within 3D creation software such as Blender and/or Unity. This processing enabled the creation of simulations depicting the long cane's movements. These simulations could then be visualized on a screen using an avatar specially created within the software.

While the project was originally intended to be implemented on Unity, understanding the interoperability between Blender and Unity was necessary for its realization. This involved exploring the links between the two software platforms to ensure seamless integration of the simulation data.

This research area has opened up a wide range of possibilities for further research and development of interfaces in the future. This topic is currently being explored in the laboratory, as it has the potential to enable users to have specialized software tailored to their specific needs.

Chapter 10

Conclusions

1. The article compendium thesis aimed to address the challenges and limitations of IMU sensors in assistive technologies for visually impaired people, evaluate the effectiveness of a proposed low-cost motion measurement system in supporting visually impaired during rehabilitation exercises compared to existing solutions, and develop and evaluate the reliability and accuracy of wearable sensors for measuring spatio-temporal parameters of gait and posture in visually impaired. The hypothesis was that the integration of inertial wearable sensors could significantly improve the accuracy and effectiveness of mobility assessment and support for VIP.

2. The thesis proposed a simple architecture based on the use of wearable inertial sensors for quantitative estimation of spatio-temporal parameters of gait and posture in visually impaired people. The parameters were calculated using absolute orientation angles, and two different sensing architectures were tested for gait according to a selected biomechanical model. The validation tests included five different walking tasks, and there were nine visually impaired volunteers in real-time acquisitions, where the volunteers walked indoor and outdoor distances at different gait velocities. The ground truth gait characteristics of the volunteers in five walking tasks and an assessment of the sensor placed in the dorsal area were obtained.

3. The results obtained from the assessment showcased the potential of the model in facilitating a system that could significantly enhance accessibility and independence for visually impaired people who interact with machines. The positive outcomes indicated that the model could successfully identify and track products within the vending machines, thus enabling users to navigate the purchasing process more effectively. The model demonstrated promising performance and exhibited potential for integration into a larger system aimed at improving accessibility and independence for VIP when interacting with vending machines. Future work includes the development of an interface.

The findings from the thesis contribute to the ongoing research and development of deep learning-based assistive technology for VIP.
The development of a user-friendly interface for the system is identified as a key area for future work. The integration of computer vision technology into assistive systems has the potential to significantly improve the lives of VIP by enhancing their independence and accessibility in

various daily tasks and interactions. There is still much work to be done in the field, and that future research should focus on addressing the challenges and limitations of current technologies, expanding the potential uses of the technology, and assessing the long-term effectiveness of the technologies in improving the quality of life of visually impaired people.

10.1 Future Research Lines

The proposed future research lines for this doctoral thesis are:

1. The development of assistive technologies for visually impaired people in rehabilitation should focus on addressing the challenges and limitations to make the systems more robust and user-friendly. This may involve the design and implementation of user-centered interfaces and the integration of feedback mechanisms to enhance the usability of the systems.
2. The use of computer vision-based assistive technology for blind and visually impaired people in rehabilitation can be extended to other applications, such as obstacle detection and gait analysis. This may involve the development of new algorithms and the integration of additional sensors to enhance the capabilities of the systems.
3. Longitudinal studies are essential to assess the long-term effectiveness of computer vision-based assistive technology for visually impaired people in rehabilitation. This may involve the collection of data over an extended period to evaluate the impact of the systems on the mobility and independence of the users.

4. Firmware development and integration of the solutions in the inertial sensor module prototype should be done.

Addressing the challenges will help ensure that the proposed technologies are practical and effective for real-world use. Also, research the use of the system in other applications, such as obstacle detection and gait analysis, will help expand the potential uses of the technology and improve its overall impact. Also, conducting longitudinal studies to assess the long-term effectiveness of the system will help ensure that the technologies are truly making a difference in the lives of visually impaired people. These future research lines align with the current state of research in the field.

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