

Universidade do Minho
Escola de Engenharia

Luís Carlos Rodrigues Moreira

**Assist-As-Needed Control for a Smart
Orthotic System Aiming a Personalized Gait
Rehabilitation**

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**Assist-As-Needed Control for a Smart
Orthotic System Aiming a Personalized
Gait Rehabilitation**

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STATEMENT OF INTEGRITY

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Controlo de assistência conforme as necessidades para um sistema ortótico inteligente com vista à reabilitação personalizada da marcha

RESUMO

O acidente vascular cerebral (AVC) corresponde à terceira principal causa de incapacidade motora em adultos. Através de terapias de reabilitação envolvendo um treino repetitivo e personalizado ao doente, a reabilitação da marcha é essencial para a recuperação da mobilidade. Para tal, as ortóteses ativas (OAs) e exosqueletos têm sido apontados como um meio para potenciar os efeitos das terapias de reabilitação. Contudo, é crucial adaptar a reabilitação da marcha às necessidades e intenções de locomoção de cada doente, através do desenvolvimento de (i) novos sensores e algoritmos inteligentes que permitam uma avaliação objetiva da marcha; e (ii) estratégias de controlo para OAs que promovam uma terapia adaptada às necessidades de cada doente, isto é, *assist-as-needed* (AAN). Esta tese tem como objetivo expandir o SmartOs, um sistema ortótico ativo, modular e vestível, para oferecer um treino de marcha adaptado às necessidades de doentes com AVC e avaliar a locomoção através de dados cinemáticos e musculares.

A tese é estruturada em cinco passos de investigação. Primeiro, foi expandida a estrutura modular do SmartOs para integrar novos sistemas sensoriais, ferramentas de análise da marcha e estratégias de controlo. Segundo, foi criado um sistema sensorial baseado em têxteis condutores, capaz de monitorizar, simultaneamente, a atividade muscular de vários grupos musculares. O benchmarking com sistemas comerciais demonstrou o potencial deste sistema para a avaliação objetiva da contração muscular. Terceiro, foi desenvolvida uma ferramenta de *deep learning* para a descodificação de modos de locomoção, destacando-se pela sua classificação precisa e antecipativa. Quarto, foram desenvolvidas três estratégias de controlo AAN. A estratégia baseada em modos de locomoção oferece assistência de acordo com as intenções de locomoção do utilizador; a estratégia baseada em eletromiografia contribui para o fortalecimento muscular e promove a participação ativa do utilizador na terapia; e a estratégia baseada em energia visa adaptar o controlo do dispositivo para reduzir o custo metabólico do utilizador. Por fim, foram conduzidos dois casos de estudo para determinar os efeitos do sistema SmartOs como ferramenta de reabilitação em pacientes que sofreram um AVC. Em suma, os resultados indicam que o sistema SmartOs está apto para aplicação em ambiente clínico, tanto como uma solução personalizada de assistência, como uma ferramenta de avaliação da marcha em pacientes que sofreram um AVC.

Palavras-Chave: assistência e reabilitação da marcha, descodificação de modos de locomoção, estratégias de controlo, exosqueletos, inteligência artificial, sensores vestíveis.

ABSTRACT

Stroke is the third leading cause of motor disability in adults. Through rehabilitation therapies involving repetitive and user-oriented training, gait rehabilitation is essential to regain mobility. To this end, active orthoses (AOs) and exoskeletons have been identified as a means to enhance the effects of rehabilitation therapies. However, it is crucial to adapt gait rehabilitation to the specific needs and locomotion intentions of each post-stroke patient through the development of (i) new sensors and intelligent algorithms that allow an objective assessment of gait; and (ii) control strategies for AO that promote therapy tailored to the needs of each post-stroke patient, i.e., assist-as-needed (AAN). This Ph.D. thesis aims to extend SmartOs, an active, modular, and wearable orthotic system, to provide gait training adapted to the needs of post-stroke patients and to assess locomotion through kinematic and muscular data.

The thesis is divided into five research steps. Firstly, the modular structure of SmartOs was extended to integrate new sensory systems, gait analysis tools, and control strategies. Secondly, a sensory system based on conductive textiles was developed, capable of simultaneously monitoring the muscular activity of several muscle groups. Benchmarking with commercial systems demonstrated the potential of this system for objective assessment of muscle contraction. Thirdly, a deep learning tool was developed to decode locomotion modes, which is characterized by its accurate classification and predictive nature. Fourth, three AAN control strategies were developed. The AAN Locomotion Mode-driven trajectory control provides assistance according to the user's locomotion intentions. The AAN EMG-based control contributes to muscle strengthening and promotes the user's active participation in therapy. The AAN Human-in-the-Loop control aims to adapt the control of the device to reduce the user's energy expenditure. Finally, two case studies were conducted to determine the effects of the SmartOs system as a rehabilitation tool for post-stroke patients. In short, the results indicate that the SmartOs system is suitable for use in a clinical environment, both as a personalized assistance solution and as a gait assessment tool for patients who have suffered a stroke.

Keywords: Gait assistance and rehabilitation, locomotion mode decoding, control strategies, exoskeletons, artificial intelligence, wearable sensors

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List of abbreviations and acronyms

A

AAN	Assist-As-Needed
ACC	Accuracy
ADC	Analog-to-Digital Converter
AI	Artificial Intelligence
AO	Active Orthosis
API	Application Programming Interface

B

BBS	Berg Balance Scale
BI	Bartel Index

C

CAN	Control Area Network
CCU	Central Control Unit
CNN	Convolutional Neural Network
CPG	Control Pattern Generator

D

DL	Deep Learning
----	---------------

E

EGPR	Exponential Gaussian Process Regression
EMG	Electromyography

F

FAC	Functional Ambulation Classification
FEL	Feedback-Error Learning
FIM	Functional Independence Measure
5MWT	5-Meter Walk Test
FMA-LE	Fugl-Meyer Assessment – Lower Extremity
FSR	Force Sensing Resistor

H

HAI	Hauser Ambulation Index
HIL	Human-in-the-Loop

I

IMU Inertial Measurement Unit

K

KPI Key Performance Indicator

L

LGW Level-Ground Walking

LM Locomotion Mode

LOSOCV Leave-One-Subject-Out Cross-Validation

LSTM Long Short-Term Memory

M

MAS Modified Ashworth Scale

MCC Matthew's Correlation Coefficient

MI Motricity Index

MMG Mechanomyography

MMSE Mini-Mental State Examination

MRCS Medical Research Council Scale

MSD Musculoskeletal Disorder

MSE Mean Square Error

MVC Maximum Voluntary Contraction

N

NIHSS National Institute of Health Stroke Scale

O

OB Objective

P

PAFO Powered Ankle-Foot Orthosis

PID Proportional Integral Derivative

PKO Powered Knee Orthosis

R

r Spearman Correlation coefficient

R^2 Coefficient of Determination

RA Ramp Ascent

RD	Ramp Descent
RMI	Rivermead Mobility Index
RMS	Root Mean Square
RMSE	Root Mean Square Error
ROM	Range of Motion
RQ	Research Question

S

SA	Stair Ascent
SD	Stair Descent
SIAS	Stroke Impairment Assessment Set
Sit	Sitting
6MWT	6-Minute Walk Test
SmartOs	SMART control of a sTand-alone active Orthotic System
St	Standing
STD	Standard Deviation

T

10MWT	10-Meter Walk Test
TCP/IP	Transmission Control Protocol/Internet Protocol
TCT	Trunk Control Test
TRL	Technology Readiness Level
TUG	Timed Up and Go Test
2MWT	2-Minute Walk Test

U

UART	Universal Asynchronous Receiver/Transmitter
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1. INTRODUCTION

This Ph.D. thesis presents the research developed in the last four years in the scope of the doctoral program in Biomedical Engineering. The investigation was developed in the Biomedical Robotic Devices Laboratory (BiRDLAB) at the Center for MicroElectroMechanical Systems (CMEMS) established at the University of Minho, together with the Centro Clínico Académico de Braga (2CA – Braga), a partnership between the University of Minho and Braga Hospital, which provides the expertise, equipment, facilities, and access to patients and clinicians.

The developed activities have been included in the project SmartOs – SMART control of a sTand-alone active Orthotic System (POCI-01-0247-FEDER-039868). In addition, this research extends beyond a research grant (UMINHO/BI/83/2020), a Master's thesis [1], and a Ph.D. thesis [2] by proposing **Assist-As-Needed (AAN) control strategies** for a wearable orthotic system in an attempt to restore the functional lower limb motor abilities of stroke survivors. This Ph.D. thesis addresses the nexus of assistive control strategies, wearable assistive devices, artificial intelligence (AI), and human gait analysis to **personalize the assistance of the wearable orthotic system according to the user's needs and locomotion intentions to promote post-stroke recovery**.

1.1 MOTIVATION

Walking is one of the most daily performed human motor tasks. However, human gait can be compromised due to neurological diseases, such as stroke. According to the World Health Organization, **stroke events** correspond to the second leading cause of death and the **third leading cause of disability globally** [3]. Studies have reported around 13.7 million new incident cases of stroke in the world in 2016 (between 121 and 151 per 100.000 people only in Portugal) [4]. The annual economic cost of stroke in Europe is around 60 billion euros, representing 0.36% of the European Gross Domestic Product (nearly 0.40% for Portugal) [5], [6].

Based on the study [7], **more than 80% of stroke survivors present gait dysfunction** due to muscle weakness, asymmetrical gait pattern, pain, spasticity, or a loss of motor control of the lower limbs. Consequently, **the patient's quality of life is affected** since they cannot perform their daily locomotion activities (e.g., walking, running, standing, sitting, turning, and climbing stairs/ramps), or their accomplishment is difficult. These limitations commonly result in **social and work exclusion, costly medical assistance, and early retirement** [8].

There is an extreme necessity for **improving the quality of life of post-stroke patients**. Conventional physical rehabilitation provided by physiotherapists has been widely applied to face long-

term motor disabilities of these neurologically injured patients [9]. Nonetheless, lower limb rehabilitation in the last years has acknowledged the need to deal with (i) the disadvantages associated with the **inter- and intra-therapist variances**; (ii) the dependency on the malleability of the patient's joint (commonly affected by **spasticity**); and, (iii) the **absence of precise, user-oriented, and personalized assistance** during therapy [10]. In addition, recent studies have identified the costs of rehabilitating patients who have survived a stroke [11], [12]. These costs are divided into inpatient and outpatient rehabilitation costs. **Inpatients** are patients who stay in the hospital and receive medical treatment, as well as food and accommodation in a hospital. **Outpatients** are patients who do not require hospitalization. An outpatient visits a hospital, clinic, or similar facility for a diagnosis, treatment, or procedure and may leave. According to the study [11], the cost of rehabilitation therapies for outpatients is typically three times lower than for inpatients. While the largest contributor to inpatient rehabilitation costs is the cost of stay (34%), **the second largest contributor is the cost of physical rehabilitation (16%)**. In the case of outpatients, **physical rehabilitation corresponds to the largest contributor to the rehabilitation costs (26%)**. Considering the mentioned topics, in the rehabilitation area, **robotic assistance** driven by wearable assistive devices, such as **exoskeletons and active orthoses (AOs)**, has steadily gained importance [10].

According to the study [2], rehabilitation therapies driven by exoskeletons may improve the patient's muscular strength, movement coordination, and balance control, fostering the patient's ambulation and performance for successful locomotion. Accordingly, the **use of wearable assistive devices as a complementary rehabilitation tool for conventional physical rehabilitation strategies** may empower the long-term functional motor recovery of patients with lower limb impairments, **fostering their confidence and independence** by providing daily assistance [13]–[18]. Furthermore, when it comes to comparing the cost of rehabilitation between conventional therapy and robotics-guided therapy, a recent study concluded that in 80% of the cases analyzed, **robotics-guided therapy was more cost-effective than conventional therapy** [12]. Although some wearable assistive devices can cost several hundred euros, their use in rehabilitation therapies can increase the efficiency of the therapist's work, meaning that more patients can be treated, leading to an overall reduction in the cost of treatment per patient.

1.2 PROBLEM STATEMENT

Despite becoming a prominent intervention to tackle the necessity of physical rehabilitation therapies, **most of the available exoskeletons present poor usability and do not deliver personalized assistance** according to the patient's needs and intentions to move [19]–[26].

Additional imperative developments include exploring variants of **AAN control strategies** to face the limitations of the typically adopted trajectory-tracking control strategies [27]–[31]. Despite the repetitive nature of gait training imposed by trajectory-tracking control strategies, they tend to ignore the human-robot interaction and the needs of each user. As a result, these strategies may limit motor relearning and end up being abandoned [27], [28]. The development of adaptive and compliant control strategies is fundamental to **timely personalize assistive trajectories according to the user's motor needs**, and consequently, assist the users as much and when needed. At this level, AAN control strategies are needed to dynamically adjust the level of assistance based on the user's real-time muscular performance and participation ability, ensuring that the wearable assistive device assists movement without overcompensating. The goal is to **encourage the user's active participation and muscle engagement**, thereby promoting improvements in strength and motor function over time [29]–[31]. In order to capture the user's muscular performance and participation ability, electromyography (EMG) signals have been employed in AAN EMG-based control strategies. Although promising, most of the AAN EMG-based control strategies were developed for upper limbs [32]–[34]. And those developed for the lower limbs were not designed to assist the entire gait cycle, but rather focus on isolated flexion and extension movements [28], [35]–[38].

In addition, current challenges in personalized robotics-based assistance are related to **decoding different locomotion modes (LMs)** with a non-intrusive sensor setup to timely trigger the assistance delivered by wearable assistive devices according to the user's locomotion intentions (i.e., AAN LM-driven controls). Despite recent advancements, most of the current AAN LM-driven controls integrated into wearable assistive devices (i) address a limited number of daily LMs (are non-generic tools) [19], [39]; (ii) present high recognition delays, classifying and assisting the LM only after the user has already transitioned to the new LM [20], [21], [40]–[44]; (iii) do not account for the typically slower gait speeds of individuals with lower limb disabilities, since studies addressed self-selected and/or fixed speeds of healthy participants (typically above 2.7 km/h) [20], [21], [45], [46]; and (iv) do not present clinical evidence [19]–[22]. It is of the utmost importance that wearable assistive devices tackle these limitations by including algorithms and AAN LM-driven controls capable of **accurately and timely decoding**

different LMs to provide personalized assistance. If the user's LMs cannot be properly well-determined, the exoskeleton assistance may be affected [42], [47].

Furthermore, recent variations of AAN approaches include **human-in-the-loop (HITL) control strategies**, using the user's energy expenditure as a means of adapting the assistance provided by the wearable assistive device [31], [48]. By tailoring the assistance to the user's current physical state and activity level, these control strategies aim to **improve overall comfort, performance, and endurance** during the wearable assistive device's use [31], [49]–[51]. However, despite the promising performance, the available method for estimating energy expenditure is indirect calorimetry, which uses non-portable equipment, is time-consuming, produces noisy estimates, and is impractical for real-world applications [52].

In addition, most wearable assistive devices present a poor clinical evidence base, characterized by a lack of studies evaluating the longitudinal and follow-up effects of robotic therapies. There is a high number of studies that do not follow a randomized controlled procedure and do not comprehensively assess the effects of wearable assistive devices at kinematic, physiological, and functional levels [53]–[60].

This Ph.D. thesis intends to tackle the challenges mentioned above using a **smart orthotic system – SmartOs system**, in an attempt to provide new insights and innovative research directions for post-stroke rehabilitation using wearable assistive devices.

1.3 GOALS

This innovative multidisciplinary Ph.D. thesis focuses on **developing AAN control strategies and their integration into the SmartOs system**, to promote personalized assistance automatically adapted according to the patient's physiological needs and locomotion intentions.

For this purpose and considering the main goal of this thesis, there are six objectives to be pursued:

- **Objective 1: To review the effects of lower limb assistive devices in post-stroke gait rehabilitation.** This review aims to identify the wearable assistive devices already applied in the rehabilitation of post-stroke patients, as well as the joints typically assisted, the sensors used, and the control strategies employed. It also focuses on extracting information on the characterization of post-stroke patients, study design, protocols used, and clinical outcomes. The review concludes by highlighting the benefits of using wearable assistive devices in rehabilitation sessions for post-stroke patients. The

key performance indicator (KPI) 1 for this objective is a critical analysis of the main outcomes of wearable assistive devices in post-stroke patients. Chapter 2 addresses this objective.

- **Objective 2: To define the new sensing and assistance functionalities to include in the SmartOs system**, following the existing modular structure. The new system functionalities address (i) the required sensors to monitor muscle contraction and to decode LMs of post-stroke patients in real-time; (ii) gait analysis tools (such as determining the participation level, decoding locomotion intentions, and estimating energy expenditure) needed to infer the post-stroke patient performance in real-time, providing valuable information for control strategies; and (iii) AAN control strategies. This will maximize a device close to the market and its acceptability. Chapter 3 addresses this objective.
- **Objective 3: To develop a wearable sensor system to monitor muscle contraction**, exploring mechanomyography (MMG) e-textile sensors embedded into a flexible and elastic wearable band. This sensor will deal with the limitations of commonly used EMG sensors, typically affected by (i) sweating; (ii) the need for being in direct contact with the user's skin; and (iii) the need for as many sensors as the number of muscles to be monitored. The proposed sensor will be designed to simultaneously monitor and discriminate muscle contractions across different muscle groups. This objective is measured by KPI 2, considering the validation of the proposed sensor system on at least 10 healthy participants, achieving a minimum Spearman Correlation coefficient of 0.70 with a commercial EMG system, during muscle contraction. Chapter 4 addresses this objective.
- **Objective 4: To develop an LM decoding tool** by exploring the best fusion between sensor data (such as kinematic and EMG) and Deep Learning (DL) algorithms, by extending the previous teamwork [61]. This tool will be designed to timely decode the user's LMs using a minimum number of wearable sensors, in an attempt to be easily reproducible in different contexts and to overcome real-time constraints. The LM decoding tool will be the basis for assistive control strategies according to the user's locomotion intention. This objective is measured by KPI 3, considering: (i) the development of an LM decoding tool with an accuracy closer to 99.7% ([62]) for decoding four LMs and its integration into a wearable assistive device; and (ii) the real-time

validation of the proposed LM decoding tool on at least two healthy participants and one post-stroke patient, considering different gait speeds and scenarios. Chapter 5 addresses this objective.

- **Objective 5: To design, develop, and validate closed-loop AAN control strategies to adaptively and safely generate personalized assistive commands according to the user's real-time needs and locomotion intentions.** Three assistive strategies will be explored. Firstly, an AAN control based on the user's LM decoding (AAN LM-driven trajectory control) will be developed to assist users in their daily locomotion activities. The LM decoding algorithm (Chapter 5) will provide valuable information for generating and adjusting the reference trajectories according to the user's locomotion intentions. Secondly, an AAN EMG-based control strategy will be implemented to encourage the users' participation measured through muscular activity while correcting their kinematic gait patterns. This topic will extend the previous teamwork [63]–[66] by developing DL-based models to estimate ankle joint torques based on EMG signals. Thirdly, an AAN HITL control strategy that automatically adjusts the control parameters of the human-orthosis interaction (torque trajectory) using optimization algorithms will be investigated to reduce the energetic impact of using SmartOs. This objective is measured by KPI 4, considering: (i) the validation of the LM-driven trajectory control on at least two healthy participants under different gait speeds and scenarios, with adaptation of the SmartOs system assistance before the new LM has started [43], [44]; (ii) the validation of the AAN EMG-based control on at least five healthy participants with a maximum Root Mean Square Error (RMSE) of 5.9° and a maximum delay of 260 ms [2]; and (iii) the validation of the AAN HITL control on at least three healthy participants, verifying that the SmartOs system requires less than 24 minutes to find the optimal control parameters that lead to a reduction in energy expenditure [67]. Chapter 6 addresses this objective.
- **Objective 6: To evaluate the motor effects of the SmartOs system in post-stroke rehabilitation.** This objective aims to assess the longitudinal and follow-up effects (approaching kinematic and physiological measures) of using the SmartOs system in post-stroke patients by carefully outlining: (i) eligibility criteria; (ii) clinical protocols; and (iii) relevant scenarios for conducting validation studies. This objective is measured by KPI 5, considering: (i) the development of eligibility criteria and clinical protocols for

conducting rehabilitation therapies with the SmartOs system designed for post-stroke patients; and (ii) the quantification of the main sensor-based and clinical outcomes of using the SmartOs system during the rehabilitation of at least two post-stroke patients Chapter 7 address this objective.

1.4 RESEARCH QUESTIONS

The proposed ideas outline the multidisciplinary research conducted in this Ph.D. thesis, aiming to advance the use of SmartOs as a wearable assistive device for gait rehabilitation. This will enable personalized walking assistance, helping stroke survivors regain functional autonomy and improve their quality of life in the near future.

With this research project, **four Research Questions (RQs)** were identified and expected to be answered to complete the main challenges of the proposed ideas:

- RQ1: How can e-textiles be used to monitor the muscular contraction of several muscles simultaneously? This RQ is related to **Objective 3** and is answered in **Chapter 4**.
- RQ2: What fusion of sensor data and AI algorithms yields the most effective decoding of daily LMs using AO considering time and accuracy? This RQ is related to **Objective 4** and is answered in **Chapter 5**.
- RQ3: How to select the control parameters of wearable assistive devices to provide AAN training according to the user's physiological needs and locomotion intentions? This RQ is related to **Objective 5** and is answered in **Chapter 6**.
- RQ4: What are the spatiotemporal, physiological, and kinematic effects of rehabilitation therapies applied to post-stroke patients using the SmartOs system? This RQ is related to **Objective 6** and is answered in **Chapter 7**.

With the accomplishment of these RQs, it is expected to contribute to (i) long-term functional motor recovery of post-stroke patients by improving their gait pattern, muscular strength, and energetic efficiency locomotion, with consequent benefits on improved patient confidence, motor autonomy, physical and social well-being, and quality of life; and (ii) the sustainability of healthcare system, by decreasing the overall treatment duration per patient, and resource costs. Figure 1.1 summarizes the expected impact of this work.

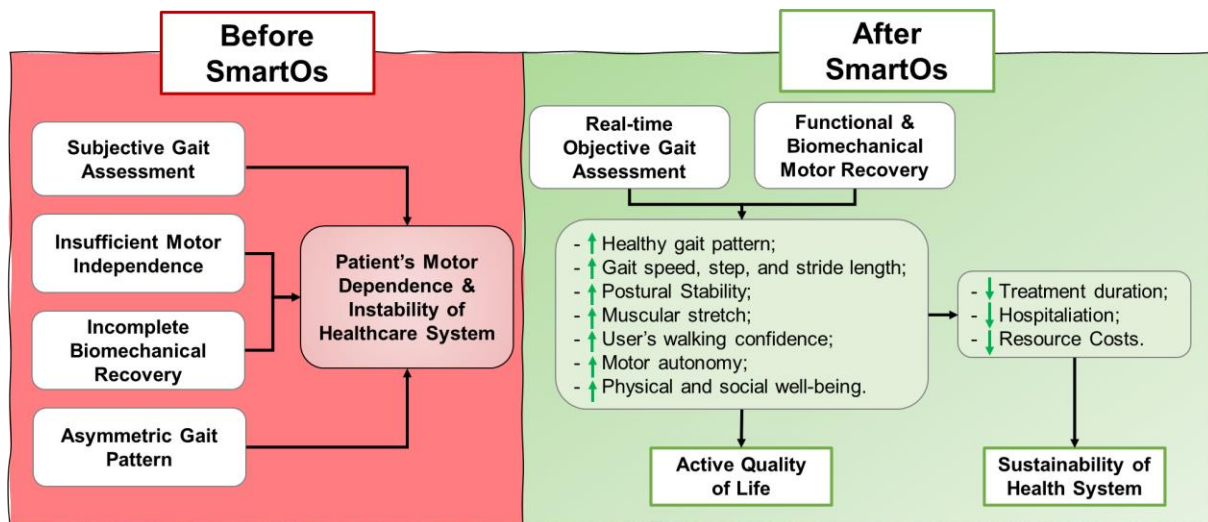


Figure 1.1 – Expected impact of the SmartOs system.

1.5 CONTRIBUTIONS TO KNOWLEDGE

This Ph.D. thesis progresses the SmartOs system, a smart, wearable orthotic system designed to interact and cooperate closely with humans. This technological solution includes an ankle AO connected to a wearable motion lab and incorporates gait analysis tools and AAN control strategies, with implications for gait rehabilitation and diagnostics of post-stroke patients.

The main contributions outlined in this Ph.D. thesis are:

- A systematic review highlighting the **main effects** of lower limb assistive devices in the **gait rehabilitation of post-stroke patients** and **current challenges to overcome** (Chapter 2 and Objective 1).
- The expandability of the SmartOs system, incorporating a new wearable sensor system, gait analysis tools, and assistive control strategies to **monitor and assist post-stroke patients** according to their needs (Chapter 3 and Objective 2).
- A stand-alone, self-calibration, **e-textile sensor system (MuscLab)** integrated into a flexible and elastic textile band to simultaneously monitor and discriminate muscle contractions across different muscle groups. This represents a cost-effective sensor system with extensive potential for versatile analysis of human movement and posture (Chapter 4 and Objective 3).
- A benchmarking analysis reporting the **best fusion between sensor features** (EMG and kinematic) **and DL algorithms** that yield the most effective **decoding of four daily LMs** [standing (St), level-ground walking (LGW), stair descent (SD), and stair

ascent (SA)] in terms of time and accuracy, **when using the SmartOs system** under variations of scenarios and gait speeds (Chapter 5 and Objective 4).

- Two locomotion datasets containing: i) **muscle activity** of eight lower limb muscles and **kinematic data**, including 3D raw accelerometer and gyroscope data of lower limb segments, and lower limb joint and segment angles. Data were collected from fifteen able-bodied **participants performing a series of motion tasks** such as St, LGW, SA, and SD in three different scenarios (indoor and outdoor) at self-selected and controlled speeds (from 1.0 to 1.6 km/h) (Chapter 5 and Objective 4); and (ii) **muscle activity** of eight lower limb muscles, **kinetic data**, including 3D ground reaction forces and joint torques of lower limb joints, and **kinematic data**, 3D lower limb joint angles during **level-ground walking at controlled gait speeds** (ranging from 1.0 to 4.0 km/h) (Chapter 6 and Objective 5).
- Two DL-based regressors for **estimating ankle joint torque trajectories**, in offline and real-time. This contributes to a more time-effective solution enabling a promising advancement in EMG-based torque controls for lower limb assistive devices (Chapter 6 and Objective 5).
- **Three AAN control strategies** to foster personalized gait training while considering the user's needs and LMs. Firstly, **AAN LM-driven trajectory control** enables the adaptation of reference trajectories for the SmartOs system according to the user's intended movements. Second, **AAN EMG-based control** automatically adjusts user-oriented trajectories and assistive commands, according to the user's muscular performance and level of participation. Third, **AAN HITL control** automatically adjusts the dynamic properties of the human-orthosis interaction (torque trajectory) using optimization algorithms to reduce the energetic impact of using SmartOs (Chapter 6 and Objective 5).
- **Two case studies reporting on the main motor effects of the SmartOs system in the gait rehabilitation process of post-stroke patients.** The physiological, kinematic, and functional effects were assessed through longitudinal studies (Chapter 7 and Objective 6).

1.6 PUBLICATIONS

The work developed in this Ph.D. thesis allowed the publication of the following journal articles and conference papers:

Journal Articles

- **Luís Moreira**, Joana Figueiredo, Pedro Fonseca, João Paulo Vilas-Boas, Cristina P. Santos, “Lower limb kinematic, kinetic, and EMG data from young healthy humans during walking at controlled speeds”, *Scientific Data*, vol. 8, 2021. DOI: 10.1038/s41597-021-00881-3. (IF: 8.5)
- **Luís Moreira**, Joana Figueiredo, João Paulo Vilas-Boas, Cristina P. Santos, “Kinematics, Speed, and Anthropometry-Based Ankle Joint Torque Estimation: A Deep Learning Regression Approach”, *Machines*, vol. 9, 2021. DOI: 10.3390/machines9080154. (IF: 2.9)
- **Luís Moreira**, Joana Figueiredo, Cristina P. Santos, “A Review on Locomotion Mode Recognition and Prediction When Using Active Orthoses and Exoskeletons”, *Sensors*, vol. 22, 2022. DOI: 10.3390/s22197109. (IF: 3.8)
- **Luís Moreira**, Joana Figueiredo, Cristina P. Santos, “Real-time Locomotion Mode Prediction Tool and Assistive Control for an Ankle Orthosis”, *IEEE Transactions on Medical Robotics and Bionics*, (under review). (IF: 3.4)
- **Luís Moreira**, Joana Figueiredo, Cristina P. Santos, “Musclab – An e-textile-based Flexible and Elastic Band to Monitor Muscle Contraction”, *IEEE Sensors Journal*, (under review). (IF: 4.3)
- **Luís Moreira**, Joana Figueiredo, João Cerqueira, Cristina P. Santos, “A pilot study on the kinematic, physiological, and spatiotemporal effects of therapy with an active ankle-foot orthosis in post-stroke patients”, *Journal of Neural Engineering*, (under review). (IF: 3.7)
- **Luís Moreira**, Joana Figueiredo, Cristina P. Santos, “Optimizing Ankle Exoskeleton Assistance through Human-in-the-Loop Control to Reduce Energy Expenditure and Muscular Effort”, *IEEE Transactions on Control Systems Technology*, (under review). (IF: 4.9)

Conference Papers

- **Luís Moreira**, Roberto Martins Barbosa, Joana Figueiredo, Pedro Fonseca, João Paulo Vilas-Boas, Cristina P. Santos, “Real-Time Torque Estimation Using Human and Sensor Data Fusion for Exoskeleton Assistance”, *The Sixth Iberian Robotics Conference (ROBOT2023)*, Coimbra, 2023.
- **Luís Moreira**, Joana Figueiredo, João Cerqueira, Cristina P. Santos, “A Real-time Kinematic-based Locomotion Mode Prediction Algorithm for an Ankle Orthosis”, *24th IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC)*, Paredes de Coura, 2024.
- **Luís Moreira**, Joana Figueiredo, João Cerqueira, Cristina P. Santos, “Assist-As-Needed Electromyography-based Control for a Wearable Ankle Robotic Orthosis”, *IEEE RAS EMBS 10th International Conference on Biomedical Robotics and Biomechatronics (BioRob 2024)*, Heidelberg, 2024.

1.7 MANUSCRIPT OUTLINE

This Ph.D. thesis is organized into eight chapters, as illustrated in Figure 1.2. **Chapter 2** provides a comprehensive review of the clinical evidence of using lower limb assistive devices in post-stroke gait rehabilitation. It covers the joints typically assisted, the control strategies employed, the sensors used, post-stroke patient characterization, study design, protocols, and both sensor-based and clinical outcomes. **Chapter 3** details the design of the SmartOs system, highlighting the proposed advances in the architecture developed in the previous study [2]. This includes the integration of a new wearable sensor system, gait analysis tools, and AAN control strategies into the SmartOs framework. **Chapter 4** presents the development and validation of a wearable sensor system (the MuscLab system) to monitor muscle contraction, utilizing e-textile sensors embedded in a flexible and elastic wearable band. **Chapter 5** focuses on the development, integration, and validation of an LM decoding tool to decode four LMs (St, LGW, SA, and SD), in real-time. It also includes a benchmark analysis to identify the best fusion of sensor features and DL algorithms for effective decoding of daily LMs. **Chapter 6** presents the three proposed AAN control strategies, detailing the design, methodology, and validation of each controller developed for the SmartOs system. **Chapter 7** introduces the clinical protocol developed and states the physiological, kinematic, and functional effects of using the SmartOs system in rehabilitation therapies for post-stroke

patients. **Chapter 8** summarizes the main findings and conclusions of the Ph.D. thesis, together with directions for future research and opportunities for technical improvement.

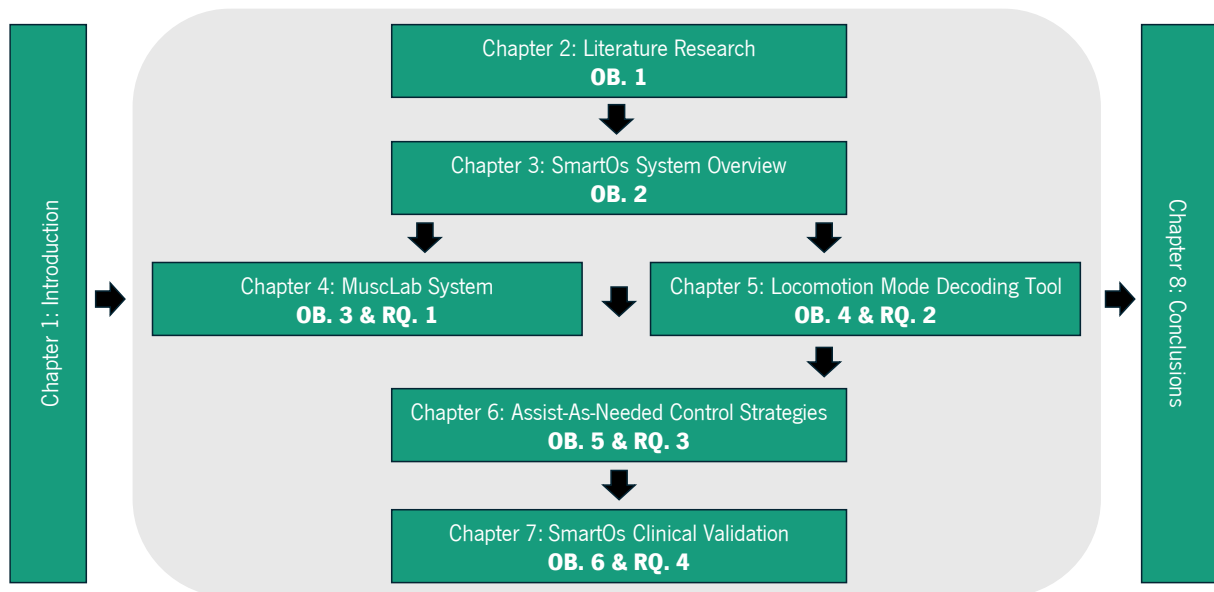


Figure 1.2 – Ph.D. thesis organization. OB. and RQ. represent objective and research question, respectively.

2. LITERATURE RESEARCH

2.1 INTRODUCTORY INSIGHT

Stroke is one of the leading causes of motor disability in adults, and those affected often face profound and lasting neurological consequences [3]. According to the study [68], 50% of post-stroke patients are initially unable to walk, 12% can walk with assistance, and 38% can walk independently. Post-stroke patients who are able to walk, experience a gait pattern that is commonly different from that of healthy individuals and that is associated with a higher risk of falling. This phenomenon is highly associated with **hemiparesis allied to joint spasticity** [69], [70]. Spasticity is a common sequela in stroke survivors, often leading to various deformities and changes in posture and movement patterns due to the abnormal increase in muscle tone and stiffness [69], [70].

Ankle spasticity is among the most prevalent movement disorders following a stroke typically resulting in **equinus, varus, or equinovarus deformities** [69], [70]. **Equinus foot** deformity causes the ankle and foot to be in a **plantarflexed position**, making voluntary dorsiflexion of the ankle joint difficult. This deformity is primarily caused by **spasticity in the ankle plantar flexors** (*gastrocnemius* and *soleus* muscles). **Varus foot** deformity is a condition in which the foot is held in an **inverted position**. This abnormal alignment is primarily caused by **spasticity in both the *tibialis anterior* and *tibialis posterior* muscles**. On the other hand, an **equinovarus deformity** is characterized by **ankle plantar flexion and inversion**. It is primarily caused by **spasticity in the plantar flexors and *tibialis posterior* muscle (invertor muscle)**, with minimal to no contribution from the *tibialis anterior* (dorsiflexor muscle) [69], [70].

In addition to these different ankle deformities, post-stroke patients also reveal **changes in the physiological (EMG), kinematic, and spatiotemporal parameters** of the lower limb joints during locomotion [71]–[75]. At the physiological level, there is high **heterogeneity in the EMG signals** of post-stroke patients. This heterogeneity is found not only between individuals (inter-individual variations) but also in the same individual (intra-individual variations). Inter-individual variation may be explained by the nature of the stroke, which can affect different regions of the brain and result in different motor disabilities [7]. On the other hand, intra-individual variations may occur due to temperature variations [72]. As stated in the study [72], older and female post-stroke patients are more vulnerable to weather conditions. Although there is high variability, there are also common factors at the EMG level, namely a **reduction in the magnitude of the EMG signals** obtained from the muscles of the paretic limb, **early onset of fatigue**, and **prolonged duration of firing** during the gait cycle [71], [76].

Lower limb joint kinematics are affected as a result of irregular EMG patterns. Post-stroke patients are commonly characterized by **reduced hip extension** during the stance phase [73]. This phenomenon is a consequence of the **overactivation of the ankle plantar flexors**. The excessive activity of the ankle plantar flexors does not allow the ankle to dorsiflex as much as required. Besides, after a stroke, the length of plantar flexors is commonly decreased, which reduces the ability of these muscles to produce enough force to perform plantar flexion movements at the terminal stance phase [73]. As a result, the forward movement of the upper body is restricted and the hip joint does not extend as expected [71]. Moreover, during the swing phase, **hip flexion tends to be reduced** as a consequence of the inability to activate hip flexors and/or overactivity of hip extensors [71]. Regarding the **knee joint**, it typically presents a **reduced flexion** ability during the early-stance phase. This phenomenon is followed by knee hyperextension used as a compensatory mechanism to achieve stability [74]. At the mid-swing phase, the knee joint typically exhibits a decreased knee flexion due to **overactivity of the *rectus femoris*** and/or **weakness of the *biceps femoris*** [71]. At the same phase of the gait cycle, the **ankle joint presents a reduced dorsiflexion** due to **overactivity of the plantar flexors**. Thus, a neutral position of the ankle joint (around 0° in the sagittal plane) is not commonly verified [75]. In summary, restricted hip and knee flexion, along with decreased ankle dorsiflexion, elongates the leg length during the swing phase. This elongation decreases the foot's clearance from the floor, leading to **toe dragging** or **compensatory leg circumduction** [71].

As a consequence of EMG and kinematics being affected, the spatiotemporal performance of post-stroke patients is also compromised. At this level, the locomotion of post-stroke patients is typically characterized by a **reduced gait speed** (below 2.7 km/h [77]) and cadence, **increased stride time of the non-paretic limb**, and double support time. Moreover, the paretic limb commonly presents a **stance phase with a lower duration** and a **swing phase with a higher duration**, compared to the non-paretic limb [71].

To deal with the above-mentioned motor disabilities, physical rehabilitation interventions that promote brain plasticity may include user-oriented, task-oriented, and repetitive gait training that encourages active participation in therapy. **Wearable assistive devices**, such as exoskeletons and AOs, in conjunction **with conventional rehabilitation therapies**, may help achieve these goals [9]. These devices have been employed to restore or modify human motor function, enhancing walking ability in individuals with impaired gait due to neurological and/or motor diseases or injuries, such as post-stroke patients [78]. Recently, research into lower limb exoskeletons and AOs has surged exponentially, establishing them as prominent physical rehabilitation interventions. These devices **reduce the**

physical burden of therapists and may represent a powerful tool for **improving mobility and recovery of post-stroke patients** [79].

2.2 REVIEW OF THE EFFECTS OF LOWER LIMB ASSISTIVE DEVICES ON POST-STROKE PATIENTS

As wearable assistive devices have been incorporated into rehabilitation therapies for post-stroke patients, it is notable to consider the benefits of their use. Considering this, this review aims to identify the wearable assistive devices that have been tested in post-stroke patients, as well as the joints typically assisted, the control strategies adopted, and the sensors used. This review also focuses on extracting information regarding the characterization of post-stroke patients, study design, protocols used, and sensor-based and clinical outcomes. The review concludes by identifying the **benefits of using wearable assistive devices** in rehabilitation sessions for **post-stroke patients**.

2.2.1 SEARCH METHODOLOGY

The literature search was conducted from December 2020 to June 2024 in the Scopus, PubMed, and Cochrane databases using the following keywords: (exoskeleton OR exoskeletons OR orthos?s) AND ("post-stroke") AND ("lower-limb" OR "lower-limbs" OR "lower limb" OR "lower limbs"). This search was limited to titles, keywords, and abstracts.

Manuscripts were evaluated based on the following inclusion criteria: (i) original studies; (ii) clinical intervention including post-stroke patients; (iii) lower limb active exoskeletons/orthoses applied for gait rehabilitation. The following exclusion criteria were applied: (i) unused exoskeletons/orthoses (3 papers rejected); (ii) only one training session applied (12 papers rejected); (iii) only protocol presented (6 papers rejected); and (iv) not post-stroke patients (3 papers rejected).

Technical and clinical information data were extracted from the **selected studies**. Technical information includes (i) the exoskeleton used, actuators employed, and joint assisted; (ii) sensor systems used to adapt the assistance; and (iii) assistive control strategies adopted. On the other hand, clinical information includes (i) characteristics of post-stroke patients; (ii) the study design; (iii) the clinical protocol followed; (iv) sensor-based and clinical outcomes; and (v) clinical evidence of wearable assistive devices on post-stroke recovery.

2.2.2 RESULTS

The literature search identified 123 studies, of which 78, 21, and 19 were found in the Scopus, PubMed, and Cochrane databases and 5 papers were identified manually from the reference sections of other studies. After removing duplicates, 100 studies remained for screening. Based on their titles and abstracts, 58 papers were excluded. Consequently, 42 full-text articles were assessed for eligibility. According to the inclusion and exclusion criteria, 18 studies were finally included. Figure 2.1 depicts the PRISMA flowchart detailing this selection process.

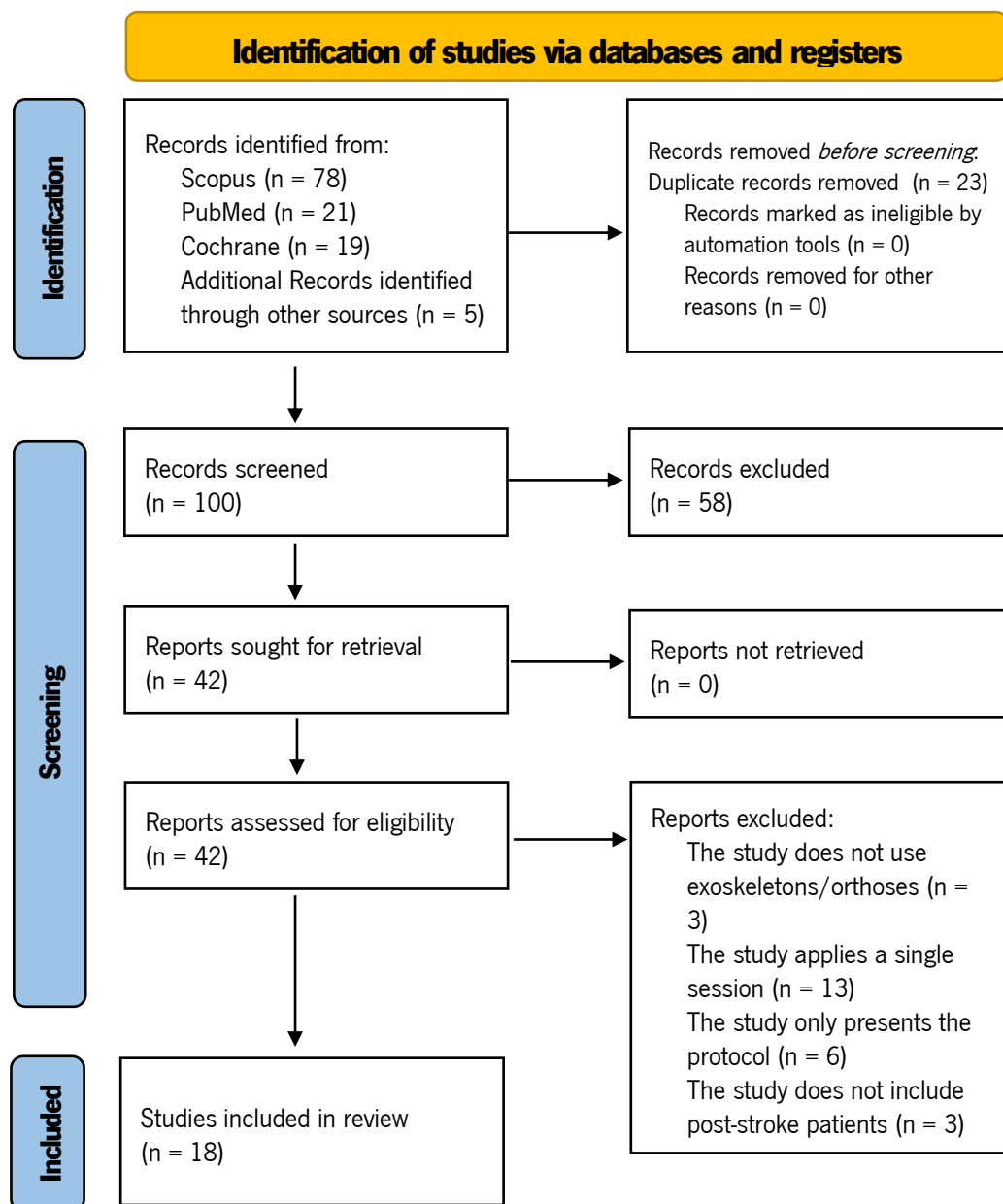


Figure 2.1 – PRISMA flowchart.

A. Technical Information

Table 2.1 summarizes the technical information extracted from the selected studies, namely, (i) the device, actuator type, and assisted joints; (ii) sensor systems; and (iii) assistive control strategies.

Device, Actuator Type, and Assisted Joints

According to Table 2.1, the effects of wearable assistive devices in post-stroke patients were studied for different devices. The most explored wearable assistive devices were the EksoNR (six studies (33.3%) [16], [54], [56], [57], [60], [80]) and the HAL (five studies (27.6%) [17], [58], [59], [81], [82]). Two studies explored the ExoAtlet [14] [15]. The effects of FreeWalk [13], H2-Exo [53], Healbot T [83], SMA [18], and a self-made active ankle-foot orthosis [55] were explored in only one study each.

Of the eighteen selected studies, seventeen used an electric motor-based actuator with gear-based transmission [13]–[18], [53], [54], [56]–[60], [80]–[83] (94.4%). Information about the actuator of the self-made active ankle-foot orthosis of the study [55] was not detailed.

Additionally, the lower limb joint typically addressed by wearable assistive devices was the hip joint (seventeen studies (94.4%) [13]–[18], [53], [54], [56]–[60], [80]–[83]), followed by the knee joint (sixteen studies (88.9%) [13]–[17], [53], [54], [56]–[60], [80]–[83]). These two joints were assisted together in sixteen studies (88.9%) [13]–[17], [53], [54], [56]–[60], [80]–[83]. The ankle joint was (i) actively assisted in two studies (11.1%) [53], [55]; (ii) passively assisted in fourteen studies (77.8%) [13]–[17], [54], [56]–[60], [80]–[82]; and (iii) not assisted in two studies (11.1%) [18], [83].

Sensor Systems

Different sensor systems were employed in the control strategy architecture of each study. Seven studies (41.2%) used Force Sensing Resistor (FSR) sensors to detect lateral and forward weight shifts [16], [54], [56]–[58], [60], [80] and to segment gait cycles [81]. Five studies (29.4%) employed EMG systems, acquiring EMG signals from *iliopsoas*, *gluteus maximus*, *semitendinosus*, and *vastus lateralis* muscles [17], [58], [59], [81], [82]. Three studies (17.6%) used embedded encoders to measure the lower limb joint angles [18], [53], [83]. Single studies have used an Inertial Measurement Unit (IMU) sensor at the trunk to segment gait cycles [57] and an interaction torque sensor [53] to determine the human-robot interaction in each lower limb joint.

Assistive Control Strategies

Several assistive control strategies were adopted by different wearable assistive devices. Of the eighteen selected studies, eight studies (44.4%) used a therapist-led step-by-step control [13]–[15], [54], [56], [57], [60], [80]. This control strategy is driven by a physical therapist who commands the steps that the user should perform by using a push button in the wearable assistive device.

Six studies (33.3%) explored the potentialities of a trajectory-tracking control based on lateral and forward weight shift [16], [54], [56], [57], [60], [80], all applied with the EksoNR. This control strategy acts as a hybrid approach in which each step is triggered by the lateral and forward weight shift of the user. Once triggered, the user follows the trajectory imposed by the wearable assistive device. In five studies (27.8%), this control strategy was adopted after the therapist-led step-by-step control, when the user learns to weight-shift to a stance position [54], [56], [57], [60], [80].

Five studies (27.8%) employed an EMG-based control [17], [58], [59], [81], [82], all applied with the HAL. This control strategy tries to find a correlation between EMG and torque signals. Once found, the controller sets assistive torque commands proportional to the EMG signals of the patient.

Two studies (11.1%) explored a trajectory-tracking control [17], [83]. With this control strategy, the wearable assistive device provides fixed assistance levels that are required to complete the desired position trajectories. The user follows the trajectory imposed by the wearable assistive device.

One study (5.6%) explored the impedance control for H2 exoskeleton [53]. When using this control type, the aim is to adjust the degree of freedom in the patient's movements by varying the interaction stiffness. Low levels of interaction stiffness allow greater freedom of movement, while high levels result in a more rigid behavior by the wearable assistive device to strictly enforce the reference trajectory. Adjusting the interaction stiffness controls the torque exerted by the wearable assistive device, thereby influencing the patient's interaction and the effort required to maintain the desired gait pattern.

One study (5.6%) used a Control Pattern Generator (CPG)-based control. This control system uses neural oscillators in addition to the user's CPG to synchronize with the user's movements. The joint angles are measured in real-time, acting as input in the controller, which assesses the joint angles' symmetry. Based on this analysis, the controller generates assistive torques at specific points of the gait cycle to improve its symmetry.

Table 2.1 – Technical details extracted from the selected studies (A, P, and NI means active, passive, and not indicated, respectively)

Study	Device	Actuator	Actuated joint			Sensor systems used in control strategies		Control strategy
			Hip	Knee	Ankle	Sensor	Measurement	
Lee <i>et al.</i> [13]	Free Walk	Electric with gear-based transmission	A	A	P	Embedded encoder		Therapist-led step-by-step exercise
Kotov <i>et al.</i> [14]	ExoAtlet	Electric with gear-based transmission	A	A	P			Therapist-led step-by-step exercise
Kovalenko <i>et al.</i> [15]	ExoAtlet		A	A	P			Therapist-led step-by-step exercise
Louie <i>et al.</i> [80]	EksoNR		A	A	P	Embedded Foot Pressure Sensor (FSR)	Lateral and forward weight shift	Therapist-led step-by-step exercise and Trajectory-tracking control based on lateral weight shift
Calabrò <i>et al.</i> [16]	EksoNR	Electric with gear-based transmission	A	A	P	Embedded FSR	Lateral and forward weight shift	Trajectory-tracking control based on lateral weight shift
Zhu <i>et al.</i> [60]	EksoNR		A	A	P	Embedded FSR	Lateral and forward weight shift	Therapist-led step-by-step exercise and Trajectory-tracking control based on lateral weight shift
Infarinato <i>et al.</i> [57]	EksoNR		A	A	P	Embedded FSR	Lateral and forward weight shift	Therapist-led step-by-step exercise and Trajectory-

Study	Device	Actuator	Actuated joint			Sensor systems used in control strategies		Control strategy
			Hip	Knee	Ankle	Sensor	Measurement	
						Inertial Measurement Unit (G-Sensor-BTS Bioengineering, Milan, Italy)	Gait cycle segmentation	tracking control based on lateral weight shift
Szurle <i>et al.</i> [56]	EksoNR		A	A	P	Embedded FSR	Lateral and forward weight shift	Therapist-led step-by-step exercise and Trajectory-tracking control based on lateral weight shift
Molteni <i>et al.</i> [54]	EksoNR		A	A	P	Embedded FSR	Lateral and forward weight shift	Therapist-led step-by-step exercise and Trajectory-tracking control based on lateral weight shift
Tan <i>et al.</i> [81]	HAL	Electric with gear-based transmission	A	A	P	Embedded EMG sensors FSR (Trigno TM 4-channel Force Sensitive Resistor)	EMG signals from <i>illio</i> psaos, <i>gluteus maximus</i> , <i>semitendinosus</i> , and <i>vastus lateralis</i> Gait cycle segmentation	EMG-based control
Lee <i>et al.</i> [83]	Healbot T	Electric with gear-based transmission	A	A	-	Embedded encoder	Hip joint angle	Trajectory-tracking control

Study	Device	Actuator	Actuated joint			Sensor systems used in control strategies		Control strategy
			Hip	Knee	Ankle	Sensor	Measurement	
Tomioka <i>et al.</i> [55]	Self-made	NI	-	-	A	NI	NI	NI
Wall <i>et al.</i> [82]	HAL	Electric with gear-based transmission	A	A	P	Embedded EMG sensors	EMG signals from <i>illioopsoas</i> , <i>gluteus maximus</i> , <i>semitendinosus</i> , and <i>vastus</i> <i>lateralis</i>	EMG-based control
Watanabe <i>et al.</i> [17]	HAL		A	A	P	Embedded EMG sensors	EMG signals from <i>illioopsoas</i> , <i>gluteus maximus</i> , <i>semitendinosus</i> , and <i>vastus</i> <i>lateralis</i>	Trajectory-tracking control and EMG-based control
Yoshimoto <i>et al.</i> [59]	HAL		A	A	P	Embedded EMG sensors	EMG signals from <i>illioopsoas</i> , <i>gluteus maximus</i> , <i>semitendinosus</i> , and <i>vastus</i> <i>lateralis</i>	EMG-based control
Bortole <i>et al.</i> [53]	H2-Exo		A	A	A	Embedded potentiometer Embedded interaction torque sensor	Hip, knee, and ankle joint angles Hip, knee, and ankle interaction torque	Impedance control

Study	Device	Actuator	Actuated joint			Sensor systems used in control strategies		Control strategy
			Hip	Knee	Ankle	Sensor	Measurement	
Buesing <i>et al.</i> [18]	SMA	Electric with gear-based transmission	A	-	-	Embedded encoder	Hip joint angles	Control Pattern Generator-based control

B. Clinical Information

Table 2.2 presents the clinical information of the selected studies, describing the (i) sample size (i.e., the number of post-stroke patients); (ii) study design; (iii) clinical protocol; (iv) sensor-based and clinical outcomes; and, (v) clinical evidence of wearable assistive devices on post-stroke recovery.

Post-stroke patients

A total of 505 post-stroke patients were involved in the eighteen selected studies. The sample size ranged from 3 [53] to 62 [15] post-stroke patients.

Overall, the post-stroke participants are typically characterized by age (typically between 18 and 80 years old) (98.4%) [13], [14], [16]–[18], [53]–[60], [80]–[83], gender (adopting a balanced gender distribution) (88.9%) [13], [16]–[18], [53]–[60], [80]–[83], time post-stroke [varying between 25 days and 6 months after stroke (sub-acute stage) and 6 months and 9.5 years after stroke (chronic stage)] (83.3%) [13], [15]–[17], [54]–[60], [80]–[83], hemiplegic side (88.9%) [13], [16]–[18], [53], [54], [56]–[60], [80]–[83], no presence of cardiopulmonary diseases (55.5%) [13], [18], [54]–[56], [59], [60], [81]–[83], and stroke etiology (50.0%) [13], [14], [16], [17], [59], [60], [80]–[82].

Less than half of the selected studies have considered post-stroke patients according to their level of cognitive function (38.9%) [13], [57], [59], [60], [81]–[83], Functional Ambulation Classification (FAC) (33.3%) [16], [17], [80]–[83], Modified Ashworth Scale (MAS) score (27.8%) [16], [56], [60], [80], [83], body mass (27.8%) [13], [17], [53], [60], [83], body height (27.8%) [13], [17], [53], [60], [83], absence of neurological conditions (as dementia, Parkinson, and depression) (27.8%) [14], [18], [55], [60], [80], absence of contractures that limit the range of motion (27.8%) [18], [54], [57], [59], [82], Mini-Mental State Examination (MMSE) score (22.2%) [14], [16], [18], [59], no evidence of pregnancy (16.7%) [57], [60], [80], Medical Research Council Scale (MRCS) (11.1%) [14], [16], ability to maintain the sitting position (11.1%) [56], [82], ability to maintain the standing position (11.1%) [57], [60], no evidence of pelvic fractures (11.1%) [60], [83], no severe osteoporosis (11.1%) [57], [83], and no evidence of infections (11.1%) [56], [60].

Single studies (5.6%) also considered the score of the National Institute of Health Stroke Scale (NIHSS) [13], Modified Rankin Scale [14], Bartel Index (BI) [14], Hauser Ambulation Index (HAI) [14], Timed Up and Go Test (TUG) [13], 10-Meter Walk Test (10MWT) [14], no use of a pacemaker [59], no orthopedic injuries [18], no uncontrolled hypertension or orthostatic hypotension [83], no second or subsequent stroke [56], no evidence of critical stenosis of great vessels of the head [14], no active deep vein thrombosis deep vein [60], and ability to transition from stand to sit and vice-versa [60].

Study Design

Considering the selected studies, ten (55.6%) were randomized controlled [13]–[18], [80]–[83], six (33.3%) were uncontrolled [53]–[58], and two (11.1%) were non-randomized controlled studies [59], [60]. In a randomized controlled study, participants are randomly assigned to either the experimental or the control group, while in a non-randomized controlled study, participants are assigned to the experimental or control groups without the use of randomization. Assignment may be based on other factors, such as participant choice, clinician decision, or other criteria. At this level, the control and experimental groups employed in the study [60] were able-bodied participants and post-stroke patients, respectively. In the study [59], participants who had limitations, such as difficulty participating regularly for eight weeks, were assigned to the control group. In addition, an uncontrolled study does not include a control group. All participants receive the same intervention, and there is no direct comparison to a group that did not receive the intervention. This means that the results achieved in studies [53]–[58] were not statistically compared to a control group.

Additionally, except for the study [83] that assigned 33 and 10 post-stroke patients to the experimental and control groups, respectively, all studies tried to guarantee an identical distribution between both groups.

Clinical Protocol

In all of the eighteen selected studies, the walking motion was the main task addressed. Only two studies [13], [16] addressed the standing up and sitting down tasks in addition to the walking task.

In the randomized and non-randomized control studies, the control group underwent conventional therapies, including physical training [13]–[18], [59], [60], [80]–[83]. On the other hand, the experimental group performed conventional therapy and therapy with the wearable assistive device [13]–[18], [53]–[60], [80], [82], [83].

Regarding the training dosing, it was collected information regarding the number of training sessions of each study, its weekly frequency, and the duration of each training session. From the reviewed studies, the average number of training sessions reported was 15.4 ± 7.55 , ranging from 8 to 60 sessions. Moreover, the average number of training sessions per week was 3.44 ± 1.22 , with the study [55] conducting 6 sessions per week (the highest frequency) and the study [59] conducting 1 session per week (the lowest frequency). Two studies [15], [83] did not indicate the number of training sessions registered per week. Concerning the duration of each session, the average time of

therapy with a wearable assistive device was 38.3 ± 15.1 minutes. This duration does not include the donning/doffing of the wearable assistive device. The maximum duration registered was 60 minutes in the studies [15], [54], [82], while the lowest one was 20 minutes registered in the studies [17], [58], [59], [81].

Sensor-based and Clinical Outcomes

Different sensor-based (55.6%) and clinical outcomes (94.4%) were employed to assess the post-stroke patients' progress. Regarding sensor-based outcomes, they can be categorized into physiological (47.4%), spatiotemporal (31.6%), and kinematic (21.0%) outcomes. The physiological outcomes consisted of the analysis of (i) EMG signals (55.6%) [16], [57], [58], [60], [81] from *tibialis anterior* (17.9%), *gastrocnemius* (14.3%), *biceps femoris* (10.7%), *rectus femoris* (10.7%), *vastus medialis* (10.7%), *semitendinosus* (10.7%), *soleus* (7.1%), *adductor longus* (7.1%), *gluteus maximus* (7.1%), and *gluteus medius* (3.7%); (ii) isometric muscle strength of quadriceps (22.2%) [13], [17]; and (iii) energy consumption (22.2%) [14], [60].

The spatiotemporal outcomes assessed in the selected studies were stance/swing ratio (20.0%) [16], [58], [60], [81]; gait speed (15.0%) [18], [58], [60], cadence (15.0%) [16], [18], [58], step length (10.0%) [18], [58], stride length (5.0%) [18], stance time (5.0%) [18], double support time (5.0%) [18], walking time (5.0%) [56], number of steps (5.0%) [56], foot clearance (5.0%) [60], gait cycle duration (5.0%) [16], and gait quality index (5.0%) [16].

The kinematic outcomes consisted of analyzing the (i) patterns of the lower limb joint angles at the sagittal plane during gait cycles [57], [60]; and (ii) the range of motion of the lower limb joint angles at the sagittal plane [58].

On the other hand, clinical outcomes assessed the motor (84.0%), post-stroke stage (10.7%), and mental (5.3%) effects. Motor effects were typically assessed by FAC (15.6%) [17], [53], [54], [57]–[59], [80]–[83], TUG (14.3%) [13], [16], [17], [53], [55], [56], [59], [60], [83], 10MWT (14.3%) [15]–[17], [54], [55], [57], [59], [60], [83], 6-Minute Walk Test (6MWT) (9.5%) [13], [17], [53], [54], [60], [80], Berg Balance Scale (BBS) (9.5%) [14], [15], [53], [59], [80], [83], BI (4.8%) [14], [53], [82], MAS (4.8%) [15], [54], [57], Motricity Index (MI) (4.8%) [54], [57], [83], Trunk Control Test (TCT) (3.2%) [54], [57], Rivermead Mobility Index (RMI) (3.2%) [16], [57], Modified Rankin Scale (3.2%) [14], [15], MRCS (3.2%) [14], [15], Functional Independence Measure (FIM) (3.2%) [58], [81], 2-Minute Walk Test (2MWT) (1.6%) [82], Tardieu Scale (1.6%) [15], 5-Meter Walk Test (5MWT) (1.6%) [80], and HAI (1.6%) [14].

The post-stroke stage effects were verified by the Fugl-Meyer Assessment – Lower Extremity (FMA-LE) (87.5%) [17], [53], [55], [58], [80]–[82], and the Stroke Impairment Assessment Set (SIAS) (12.5%) [55].

The mental effects were analyzed in single studies by the 36-item [80] and 12-item Short Survey [13], Montreal Cognitive Assessment [80], and Patient Health Questionnaire [80].

To evaluate the mentioned effects, all selected studies carried out a pre- and post-training evaluation. The studies [18], [54], [59], [81], [82] performed additional evaluations in intermediate time points between the beginning and end of the training. Moreover, the study [18] and the studies [80], [82] performed a 3-month and 6-month follow-up, respectively, to evaluate the retention of the effects.

Clinical Evidence of Wearable Assistive Devices in Post-Stroke Patients

For randomized controlled and non-randomized controlled studies, the clinical evidence was presented as improvements achieved by the experimental group (the group that performed conventional and robotic-based training sessions) over the control group (the group that carried out conventional therapy), considering the pre- and post-training time points. In the case of uncontrolled studies, the clinical evidence was evaluated by comparing the outcomes of the experimental group at the pre- and post-training time points.

Gait speed improvements were the outcome mostly referenced (27.5%) [13]–[18], [53]–[56], [58]–[60], [83], followed by improvements in the balance (11.8%) [14]–[17], [54], [59], distance walked (9.8%) [13], [17], [53], [54], [60], gait symmetry (9.8%) [16], [18], [58], [60], [81], muscle strength of the quadriceps (7.8%) [13], [14], [16], [54], and postural stability (5.9%) [14], [15], [54]. Other improvements were reported once (2.0%), such as stride length [18], step length [18], walking time [56], time of verticalization [56], number of steps [56], step cadence [58], foot clearance [60], knee flexion [16], range of motion of the hip, knee, and ankle of the non-paretic limb [58], range of motion of the hip and knee of the paretic limb [58], muscle strength of *tibialis anterior*, *gastrocnemius*, and *biceps femoris* [57]. Further, the study [14] also reported a decrease in the hemiparesis degree and energy expenditure.

Additionally, the results of the post-training for two studies [80], [82] did not report any improvements in the experimental group over the control group. Unlike the study [14], the study [60] did not show improvements in the energy expenditure. The post-training results of the study [57] did not reveal improvements in gait speed, spasticity level, and postural stability. Despite the post-training

results revealing improvements in the gait speed, balance, gait symmetry, knee flexion, and knee muscle strength, the study [16] did not find significant improvements in the muscle activity of the *tibialis anterior* and *gastrocnemius* muscles of the experimental group over the control group. Moreover, the study [58] also reported a decrease in the range of motion of the ankle joint on the paretic side.

Table 2.2 – Clinical details extracted from the selected studies

Study	Sample Size (EG/CG*)	Study design	Clinical protocol	Outcomes		Evaluation time points	Clinical evidence
				Sensor-based	Clinical		
Lee <i>et al.</i> [13]	38 (17/21)	RCT	3 times/week until 12 sessions	Quadriceps isokinetic muscle strength	Timed Up and Go Test (TUG); 6-min Walk Test (6MWT); 12-item short form survey	Pre- and post-training	Improvement of knee muscle strength, distance walked, gait speed, and quality of life
Kotov <i>et al.</i> [14]	42 (21/21)	RCT	30-min 5 times/week until 10 sessions	Vertical stability; Energy consumption	Medical Research Council (MRC); Modified Rankin Scale; Bartel Index (BI); Hauser Ambulation Index (HAI); Berg Balance Scale (BBS); 10-Meter Walk Test (10MWT)	Pre- and post-training	- Improvement of paretic limb muscle strength, balance, postural stability, and gait speed. - Decrease in hemiparesis degree and energy consumption
Louie <i>et al.</i> [80]	36 (17/19)	RCT	25-min twice/week until 24 sessions		Functional Ambulation Categories (FAC); Fugl-Meyer Assessment – Lower Extremity (FGM-LE); 5-Meter Walk Test (5MWT); 6MWT; BBS; Montreal Cognitive Assessment	Pre-, post-training, and 6-month follow-up	No improvements were found when comparing the exoskeleton-based therapy with conventional therapy

Study	Sample Size (EG/CG*)	Study design	Clinical protocol	Outcomes		Evaluation time points	Clinical evidence
				Sensor-based	Clinical		
Kovalenko <i>et al.</i> [15]	62 (31/31)	RCT	1-h/day until 10 sessions		(MCA); 36-item short form survey	Pre- and post-training	Improvement of gait speed, balance, and postural stability
					Tardieu Scale (TS); Modified Ashworth Scale (MAS); MRCS; 10MWT; Rivermead Mobility Index (RMI); BBS; Modified Rankin Scale		
Calabrò <i>et al.</i> [16]	40 (20/20)	RCT	45-min 5 times/week until 40 sessions	RMS of <i>tibialis anterior</i> , <i>soleus</i> , <i>rectus femoris</i> , and <i>biceps femoris</i> ; step cadence; stance/swing ratio; gait quality index; gait cycle duration	10MWT; RMI; TUG;	Pre- and post-training	- Improvement of gait speed, balance, gait symmetry, knee flexion, and knee muscle strength. - The <i>tibialis anterior</i> and <i>soleus</i> did not show improvements
Zhu <i>et al.</i> [60]	21 (10/11)	Non-RCT	50-min 3 times/week until 15 sessions	Energy expenditure; lower limb joint angles (hips, knees, and ankles); RMS of <i>tibialis anterior</i> ; <i>soleus</i> , <i>gastrocnemius medialis</i> ,	10MWT; 6MWT, TUG;	Pre- and post-training	Improvement of gait speed, distance walked, foot clearance, and gait symmetry.

Study	Sample Size (EG/CG*)	Study design	Clinical protocol	Outcomes		Evaluation time points	Clinical evidence
				Sensor-based	Clinical		
				<i>vastus medialis, rectus femoris, biceps femoris, semitendinosus, and gluteus medius</i> ; walking speed; foot clearance; stance/swing ratio			The energy expenditure did not show improvements
Tan <i>et al.</i> [58]	8 (8/0)	Uncontrolled	20-min 3 times/week until 9 sessions	Walking speed, cadence, step length, stance/swing ratio, range of motion of the lower limb joints (hips, knees, ankles); EMG from <i>vastus medialis, semitendinosus, tibialis anterior, gastrocnemius, adductor longus, and gluteus maximus</i>	FAC; Functional Independence Measure (FIM); FMA-LE;	Pre- and post-training	Improvement of gait speed, step cadence, gait symmetry, hip and knee range of motion of the paretic side, and hip, knee, and ankle range of motion of the unaffected side
Tan <i>et al.</i> [81]	20 (9/11)	RCT		Stance ratio between paretic and non-paretic limb; EMG from <i>vastus medialis, semitendinosus, tibialis anterior, gastrocnemius, adductor longus, and gluteus maximus</i>	FAC; FIM; FMA-Locomotion; FMA-Motor; FMA-LE	Pre-, after session 3, after session 6, and post-training	Improvement of gait symmetry

Study	Sample Size (EG/CG*)	Study design	Clinical protocol	Outcomes		Evaluation time points	Clinical evidence
				Sensor-based	Clinical		
Infarinato <i>et al.</i> [57]	8 (8/0)	Uncontrolled	5 times/week until 15 sessions	EMG from <i>tibialis anterior</i> , <i>gastrocnemius medialis</i> , <i>rectus femoris</i> , and <i>biceps femoris</i> ; knee joint angles	MAS; Motricity Index (MI); FAC; Trunk Control Test (TCT); 10MWT	Pre- and post-training	- Improvement of muscle strength at <i>tibialis anterior</i>, <i>gastrocnemius medialis</i>, and <i>biceps femoris</i> - No improvements were found in gait speed, spasticity level, and postural stability
Szurle <i>et al.</i> [56]	19 (19/0)	Uncontrolled	50-min 3 times/week until 12 sessions	Number of steps; walking time; time of verticalization	TUG	Pre- and post-training	Improvement of gait speed, number of steps, walking time, and time of verticalization
Lee <i>et al.</i> [83]	43 (33/10)	RCT	30-min/session until 10 sessions		10MWT; BBS; FAC; TUG; MI	Pre- and post-training	Improvement of postural stability, balance, and gait speed
Tomioka <i>et al.</i> [55]	27 (27/0)	Uncontrolled	40-min 6 times/week		FMA-LE; TUG; 10MWT; Stroke Impairment Assessment Set (SIAS)	Pre- and post-training	Improvement of gait speed

Study	Sample Size (EG/CG*)	Study design	Clinical protocol	Outcomes		Evaluation time points	Clinical evidence
				Sensor-based	Clinical		
			until 24 sessions				
Molteni <i>et al.</i> [54]	23 (23/0)	Uncontrolled	60-min 3 times/week until 12 sessions	MAS; MI; TCT; FAC; 10MWT; 6MWT		Pre-, after session 6, and post-training	Improvement of muscle strength, postural stability, balance, gait speed, and distance walked
Watanabe <i>et al.</i> [17]	22 (11/11)	RCT	20-min 3 times/week until 12 sessions	Isometric muscle strength at hip and knee flexion and extension movements	FAC; 10MWT; 6MWT; FMA-LE	Pre- and post-training	Improvement of gait speed, balance, and distance walked
Yoshimoto <i>et al.</i> [59]	18 (9/9)	Non-RCT	20-min once/week until 8 sessions	FAC; 10MWT; TUG; BBS		Pre-, after session 4, and post-training	Improvement of gait speed and balance
Bortole <i>et al.</i> [53]	3 (3/0)	Uncontrolled	3 times/week until 12 sessions	BBS; Barthel Index (BI); FAC; FMA-LE; TUG; 6MWT		Pre- and post-training	Improvement of distance walked and gait speed

Study	Sample Size (EG/CG*)	Study design	Clinical protocol	Outcomes		Evaluation time points	Clinical evidence
				Sensor-based	Clinical		
Buesing <i>et al.</i> [18]	50 (25/25)	RCT	45-min 3 times/week until 18 sessions	Walking speed; cadence; step time; step length; stride length; stance time; double support time		Pre-, after session 9, post-training, and 3-month follow-up	Improvement of gait speed, step time, step length, stride length, and gait symmetry
Wall <i>et al.</i> [82]	32 (16/16)	RCT	60-min 4 times/week until 16 sessions		FAC; FMA-LE; 2-minute Walk Test; BI	Pre-, post-training, and 6-month follow-up	No improvements were found when comparing the exoskeleton-based therapy with conventional therapy

*EG and CG mean experimental and control groups, respectively

2.2.3 DISCUSSION

A. Technical Information

Among various clinical trials, **EksoNR** and **HAL** were the most commonly used devices to evaluate the effects of wearable assistive device therapy in post-stroke patients. Although the use of exoskeletons for the rehabilitation of post-stroke patients has been a topic of discussion for some time, these results show that only two wearable assistive devices have featured prominently in studies designed to prove the effectiveness of these devices in post-stroke patients. Future research should address this gap by **conducting clinical trials with other devices** to investigate the benefits of each device or investigate if there are differences among them.

According to the study [53], (i) hydraulic and pneumatic actuators offer high power density but are typically bulky and prone to internal leakage and friction; (ii) series elastic actuators are limited by the fixed spring constant of their elastic elements; and (iii) electric motor-based actuators have been indicated due to its reduced power consumption during gait. These results support the findings of the studies reviewed since **electric motor-based actuators were typically adopted** for the majority of the studies.

In most of the studies, the **hip and knee joints were actively assisted** by the wearable assistive device, while the **ankle joint was passively assisted**. According to the study [71], the dorsiflexion of the ankle joint during the stance phase is restricted due to the overactivity of the plantar flexor muscles, specifically the *gastrocnemius* muscle. This limitation affects the hip joint by preventing it from extending as far as necessary. Another common kinematic issue is reduced ankle dorsiflexion during the swing phase. Normally, the ankle reaches a neutral position at the mid-swing phase and maintains this position until initial contact. Achieving a neutral ankle position at this point is crucial because it brings the foot closer to the ground, facilitating limb movement to prevent toe drag. The lack of dorsiflexion during the swing phase and at the heel-strike phase is likely caused by overactive plantar flexor muscles and insufficient dorsiflexion. As a result, post-stroke patients tend to perform leg circumduction [71]. These phenomena suggest that the ankle joint is often affected in post-stroke patients and that sometimes a kinematic change in another lower limb joint (such as the hip) is a consequence of the ankle joint being affected. Therefore, **future research** should address these issues by developing **wearable assistive devices that invoke the ankle joint to play an active role** in rehabilitation therapies.

Additionally, weight shift detections measured by **FSRs**, **EMG signals** from, *gluteus maximus*, *semitendinosus*, and *vastus lateralis* muscles, and **lower limb joint angles** measured by embedded encoders were the **most used type of data in the control strategies** of the reviewed studies. Although EMG sensors were widely used, their application was limited to the HAL device. Given the importance of these sensors in discriminating the locomotion intentions and needs of post-stroke patients, future research should address the inclusion of these sensors in the control architecture.

The **therapist-led step-by-step control** was the most used control when using wearable assistive devices, followed by the **trajectory-tracking control based on lateral and forward weight shift**. This last control strategy was typically adopted after the therapist-led step-by-step control when the post-stroke patient learned to weight-shift to a stance position. While in the therapist-led step-by-step control, post-stroke patients are commanded by the physical therapist, the trajectory-tracking control based on lateral weight shift invokes the patients' participation to continuously perform right and left steps. Nonetheless, the user's participation is only required at the beginning of each step and not for the complete gait cycle. In addition, the effect of **EMG-based control strategies** was also explored. For the wearable assistive device to move, the post-stroke patient must actively participate throughout the gait cycle, as the device provides assistance that is proportional to the level of muscle activation of the monitored muscles. Therefore, non-participation by post-stroke patients means that the wearable assistive device does not assist [37]. Despite being a valuable contribution to muscle strengthening, these EMG-based torque controls do not consider different levels of motor disabilities, nor assist the user when and as much as needed. **Future research** should address this limitation by **developing AAN control strategies** to provide the robotic assistance needed for post-stroke patients to complete a movement, taking into account their **motor impairments** and **invoking their participation**.

B. Clinical Information

Clinical trials investigating the effects of wearable assistive devices on post-stroke recovery had, on average, a diverse sample of participants, ranging from 3 to 62, which provides a benchmark for future research. Participants in these trials were primarily characterized by **age** (from 18 to 80 years old), **gender** (balanced gender distribution), **time post-stroke** (varying between sub-acute (from 25 days to 6 months) and chronic (from 6 months to 9.5 years) stages), **hemiplegic side**, **absence of cardiopulmonary disease**, and **stroke etiology**. To increase the reliability of future

studies, a quantitative characterization of the level of disability before the intervention could be included.

Most of the selected studies conducted **randomized controlled studies**, revealing an average **training dosing of 38.3 minutes/session, three times a week** until reaching an **average of fifteen training sessions**. The protocols are not usually very detailed in terms of gait speed, scenario conditions, and familiarization procedures. However, future studies should specify these procedures, as they may affect the reproducibility of the study.

The majority of the studies used **pre- and post-training evaluation points** to assess the **effects of wearable assistive devices** on post-stroke recovery using sensor-based and clinical outcomes. Few studies evaluated effects at intermediate time points during training. Retention procedures have occasionally been used to assess motor learning after training, with **follow-up assessments typically at 3 and 6 months after training**. Future studies should carry out more follow-up evaluations to examine the long-term effects of assistive devices on post-stroke patients.

When comparing sensor-based and clinical outcomes, **clinical outcomes were the most commonly assessed**. Most studies used the **FAC, TUG, and 10MWT** clinical scales to assess the motor effects of wearable assistive devices in post-stroke patients. Less than a quarter of the studies also measured the post-stroke stage and mental effects using clinical outcomes. The **FMA-LE** is the most commonly used scale to assess the post-stroke stage. Mental effects were analyzed using the 36-item and 12-item Short Surveys, the Montreal Cognitive Assessment, and the Patient Health Questionnaire. Furthermore, sensor-based outcomes typically addressed physiological effects by analyzing **EMG signals from the *tibialis anterior*, *gastrocnemius*, *biceps femoris*, and *rectus femoris***. Spatiotemporal effects such as **stance/swing ratio, gait speed, cadence**, and **stride length** have been emphasized, and kinematic effects have mainly been evaluated based on **lower limb joint angles in the sagittal plane**. Therefore, future studies should conduct user-specific assessments by including comprehensive analyses of multiple outcomes approaching kinematic, physiological, and spatiotemporal sensor-based outcomes, as well as motor, post-stroke stage, and mental effects.

Most of the selected studies showed significantly greater improvements in the experimental group than in the control group. Improvements in **gait speed** were the most commonly reported outcome, followed by improvements in **balance, distance walked, gait symmetry**, and **muscle strength of the quadriceps**. However, some studies reported no significant improvements in muscle activity of the *tibialis anterior* and *gastrocnemius* muscles of the experimental group

compared with the control group, confirmed by a decrease in ankle range of motion on the paretic side. This may be related to the passive rehabilitation that the ankle joint received during the training.

2.3 CONCLUSIONS

This literature review presented the main contributions of wearable assistive devices during the recovery process of post-stroke patients. As a result, **wearable assistive devices revealed improvements in gait speed, balance, distance walked, gait symmetry, and muscle strength of the quadriceps**. These outcomes are a result of rehabilitation therapies with wearable assistive devices during an **average of 38.3 minutes/session, three times a week, for an average of fifteen training sessions**.

Despite the referred promising results, there is room for new advancements. **There is a need for the development of more clinical trials**, preferably randomized controlled trials, not only to investigate the effects of more wearable assistive devices but also to confirm the effects that have already been reported. Future studies should also **conduct additional intermediate and follow-up evaluations** to examine the effects of wearable assistive devices in post-stroke patients during training and in the long term. The effects should be analyzed through a holistic approach, assessing kinematic, physiological, and spatiotemporal sensor-based outcomes, as well as motor, post-stroke stage, and mental effects. Moreover, future research should **specify the presence and duration of familiarization routines** with wearable assistive devices, as this procedure may impact the reproducibility of other studies.

On the other hand, more sensors, preferably wearable sensors such as EMG and IMUs, should be included in control strategies of wearable assistive devices to take into account the level of disability of post-stroke patients and their locomotion intentions. This leads to another gap in the literature, which is the **lack of control strategies that elicit post-stroke patient participation** throughout the gait cycle and across different LMs, providing assistance when and as needed (AAN controls). At this level, future studies should involve the active participation of the ankle joint in therapy, as this is one of the lower limb joints most affected by stroke.

The ongoing development of the SmartOs system, as presented in Chapter 3, aims to address the identified scientific challenges and leverage existing expertise. Continuous user involvement is crucial in designing and developing personalized solutions, as proposed by SmartOs, to ensure they align with post-stroke patients' needs and locomotion intentions.

3. SMARTOS SYSTEM OVERVIEW

This chapter describes the design and functionalities of the SmartOs system, considering the information compiled in Chapter 2. The numerous gaps and challenges identified in the area of user-centered assistance, as well as future directions, drive this thesis to develop gait analysis tools and control strategies that enable SmartOs to provide assistance oriented to the user's requirements.

The solution consists of extending the modular and hierarchical architecture developed in the study [2], by adding the ability for SmartOs to (i) track the real-time contraction of multiple muscles simultaneously using a single sensor (Chapter 4); (ii) decode multiple LMs (Chapter 5); and (iii) adapt its assistance according to the user's locomotion intentions (Chapter 6.2), muscular participation level (Chapter 6.3), and energy expenditure (Chapter 6.4).

3.1 INTRODUCTORY INSIGHT

Current technological and scientific directions in wearable assistive devices include the integration of wearable sensor systems and assistive control strategies based on gait analysis tools to promote user-oriented assistance. The SmartOs system addresses these directions. It **includes a wearable motion laboratory** with biomechanical and muscle sensors that **provide data for gait analysis tools**. The output of these tools is used by the **system's control strategies**; thus, allowing the system to **adapt to the user's needs**.

To this end, the modular structure designed and developed in the study [2] was followed, promoting the expandability of the system to other sensor systems, gait analysis tools, and assistive control strategies. The structure followed the bio-inspired principles of a hierarchical control architecture to timely adjust the level of assistance provided by the AOs according to the assessment of the user's needs and locomotion intentions, both tracked in real-time by the gait analysis tools. Further, the SmartOs framework includes graphical applications that have been updated for the intuitive configuration of SmartOs modules and functionalities and for the visual monitoring of the user's movement, respectively.

3.2 CONCEPTUAL DESIGN AND FUNCTIONALITIES

For that, the SmartOs system, depicted in Figure 3.1, employs a **non-centralized architecture**, structured as a modular and hierarchical framework, being organized into **high-, mid-, and low-levels**, as proposed in the study [9]. The main blocks of the framework consist of (i) a Central Control Unit (CCU); (ii) two user-friendly graphical applications, a mobile and a desktop application; (iii) two development boards (Wearable Motion Lab and Low-Level Orthotic System); (iv) actuators (an ankle and a knee AOs);

(v) power supply; (vi) and sensor systems. To enhance user comfort and practicality, the CCU, the two development boards, and the power supply are combined within a backpack housing the system.

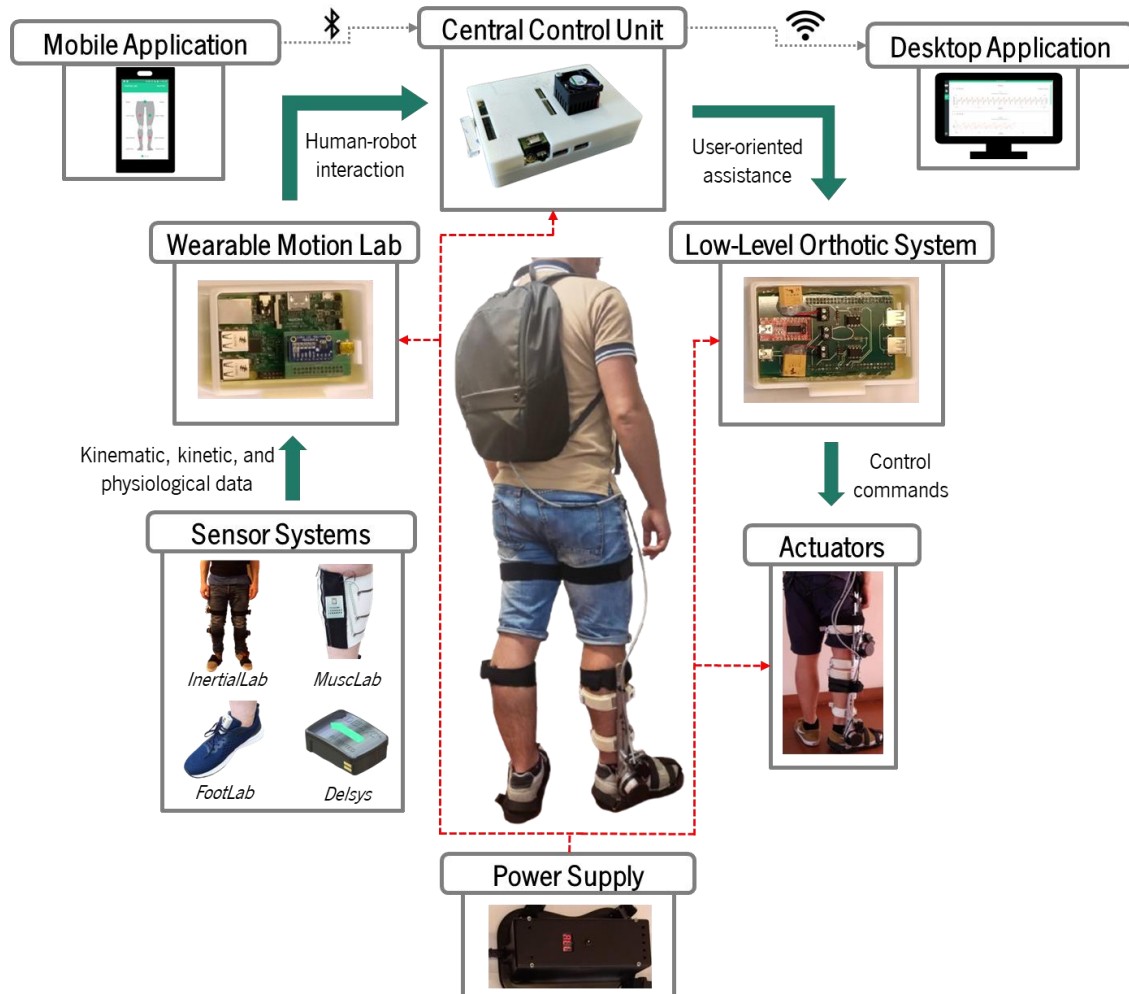


Figure 3.1 – SmartOs modular framework.

The **CCU**, running the high-level controls and executing gait analysis algorithms at 100 Hz, is implemented using a UD00 X86 computer (2.24 GHz and a Random Access Memory with 4.0 GB). The **two development boards** correspond to STM32F4-Discovery boards (STMicroelectronics, Switzerland), communicating with the CCU through a Universal Asynchronous Receiver/Transmitter (UART) interface. These development boards comprehend (i) a Wearable Motion LAB, which facilitates real-time data acquisition from **sensor systems** developed by the team [84], [85] and from external sensors [86]; and (ii) a Low-Level Orthotic System, handling mid- and low-level controllers that interface with the active orthoses (Exo-H2, by Technaid, Madrid, Spain [53]), through the Control Area Network (CAN) protocol. **The power supply system** consists of a lithium iron phosphate battery (LifePO4) with a voltage of 22.4 V and a capacity of 12 Ah. This battery provides a minimum of 8 hours of autonomy and is equipped with a hardware interface to supply power to all modules of SmartOs, operating at 5 V

and 12 V. Additionally, a **mobile graphical application** allows the user to configure the system by defining the therapy settings, user's information, and starting and stopping the therapy. At last, the **desktop graphical application** enables the visualization, in real-time, of the data collected by the Wearable Motion Lab system.

3.2.1 ACTUATORS

Currently, the SmartOs framework features the integration of two AOs, namely a **Powered Ankle-Foot Orthosis (PAFO)** for the right ankle joint and a **Powered Knee Orthosis (PKO)** for the right knee joint. These AOs are part of the lower limb **exoskeleton-H2** developed by Technaid S.L., in Spain [53]. These AOs provide support in the sagittal plane and for walking speeds between 0.5 and 1.6 km/h. Both AOs are equipped with several embedded sensors, including (i) a precision potentiometer with 0.5° resolution to measure the joint angles; (ii) four strain gauges arranged in a full Wheatstone bridge with 1 N.m resolution, assessing the interaction torque between the user and the AO; (iii) and a Hall effect sensor that tracks the actuator torque and angular velocity. Additionally, the PAFO incorporates two FSRs at the heel and toe to accurately gather information regarding the contacts with the floor.

The actuation system consists of an electrical actuator (EC60 100W Flat Brushless (Maxon, Germany), 100W and a maximum efficiency of 86 %) coupled to a gearbox (CSD-20-160-2A-GR (Harmonic Drive, Japan) with a gear ratio of 160:1, and a maximum efficiency of 55 %) able to provide an average and peak torques of 35 N.m and 180 N.m, respectively [53].

In addition, SmartOs incorporates a **wearable biofeedback system** with minimal to zero cognitive and physical effort to promote time-discrete vibrotactile/tactile and visual stimuli. It is noteworthy that the wearable biofeedback system and the PKO are out of the scope of this Ph.D. thesis. In this connection, **the PAFO is the only actuator addressed**.

3.2.2 WEARABLE MOTION LAB

The SmartOs framework incorporates a wearable motion lab, including three self-made sensor systems (**FootLab**, **InertialLab**, **MuscLab**), and a commercial sensor system [wireless 8-channel surface **EMG system** (Trigno Avanti (Delsys Incorporated, Natick, USA) [87])]. These systems correspond to **stand-alone, modular, and wearable systems** that provide valuable data from the user, in real-time, during the use of the SmartOs framework. The FootLab, MuscLab, and InertialLab

sensor systems were developed in the study [2]. However, in this Ph.D. thesis, a new version of the MuscLab system was projected and concretized (detailed in Chapter 4).

The **FootLab** consists of instrumented shoes with two IMUs (one in the upper of the shoe (LSM6DS3) and the other in the insole (LSMDSOX)) and an insole instrumented with 8 FSRs. Both sensors enable the acquisition of the foot kinematics and the creation of a pressure map on the surface of the foot, respectively. The system presents Bluetooth wireless technology and a rechargeable battery.

The **InertialLab** is composed of seven IMUs (MPU6050) positioned at the pelvis, right/left thighs, shanks, and feet, measuring the kinematics of lower limb segments.

The **MuscLab** (detailed in Chapter 4) is an e-textile designed to monitor the kinematics and the muscle contraction of muscles in a human segment. The system is made of an IMU (LSM6DS3) and piezoresistive textile strips (Shieldex® Technik-tex P130+B), integrating Bluetooth wireless technology and a rechargeable battery.

The **EMG Trigno Avanti** system integrates eight sensors that enable the acquisition of EMG muscle activity during different tasks. Each EMG sensor has a built-in triaxial IMU, composed of an accelerometer and gyroscope with a transmission range of 40 meters and a rechargeable battery. Table 3.1 summarizes the data collected by each sensor system.

Table 3.1 – Different types of data collected by each sensor system

Sensor system	Sensor data
FootLab	➤ Feet kinematics (angular speed and acceleration) ➤ Plantar pressure (pressure map)
InertialLab	➤ Kinematics (angular speed, acceleration) of lower limb segments (right and left foot, shank, thigh, trunk)
MuscLab	➤ Kinematics (angular speed, acceleration) of the shank segment ➤ Muscle contraction of the shank muscles
EMG Trigno Avanti	➤ Root Mean Square up to 8 EMG signals

In this Ph.D. thesis, the EMG Trigno Avanti system was integrated into SmartOs system by using the Trigno SDK, to enable the real-time acquisition of EMG signals during the orthosis' use [86]. For that, a Transmission Control Protocol/Internet Protocol (TCP/IP) was implemented to communicate between both systems (CCU of SmartOs system and the Base Station of Trigno Avanti system). To decrease the amount of data to be sent via TCP/IP and to work with cleaner EMG signals, the Root Mean Square (RMS) mode of the Trigno Avanti system was configured (Avanti-Only Modes: 83). This mode enables the

acquisition of rectified EMG signals with a frequency of 148 Hz, by applying the RMS method. By default, the RMS mode sends 27 EMG samples at every 0.0135 s (74 Hz). These samples are reprocessed in SmartOs system by using the RMS at 74 Hz [88]. Figure 3.2 depicts the EMG sample transmission between 1 EMG sensor and the CCU of SmartOs. As mentioned, for each EMG sensor, it is applied the RMS method to the EMG raw data collected from a specific muscle, returning a single EMG sample with a frequency of 148 Hz. These rectified EMG samples are sent in packets of 2 samples to the Trigno Avanti Base Station via a Bluetooth protocol integrated into the Trigno Avanti system, being then sent via UART to an external computer running the Trigno SDK. It is noteworthy that this external computer is only required because the Trigno SDK runs in the Windows operating system, and not in the Ubuntu operating system, which is the operating system running in the SmartOs' CCU. Subsequently, the two received EMG samples are resampled to 27 EMG samples inside the Trigno SDK, being then sent by Wi-Fi to the CCU that applies again the RMS method to retain one EMG sample with a frequency of 74 Hz.

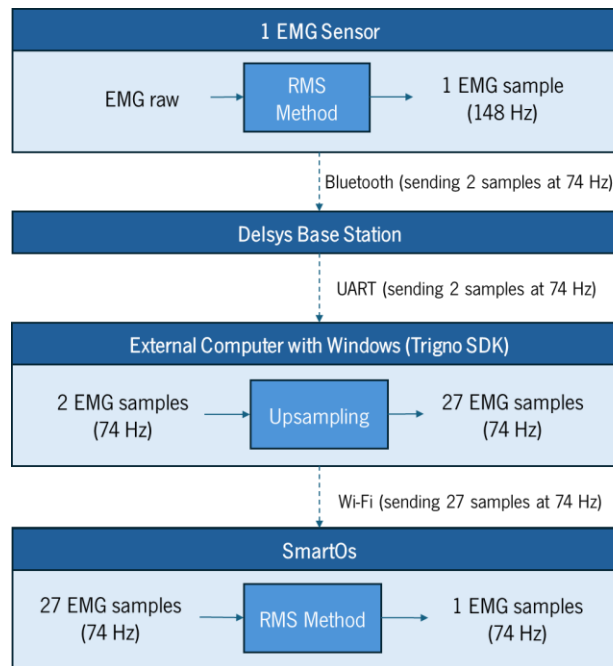


Figure 3.2 – Flowchart for acquiring RMS EMG samples with the EMG Trigno Avanti system.

3.2.3 GAIT ANALYSIS TOOLS

In the SmartOs framework, all signals measured with the wearable motion lab can be subsequently used in **gait analysis tools**. In the study [2], several gait analysis tools were developed, namely, the estimation of (i) spatiotemporal parameters (walking speed, step length, step width, stride length, distance); (ii) force parameters (center of pressure); (iii) lower limb joint angles (ankle, knee, hip) and

segment angles (foot, shank, thigh, trunk). This Ph.D. thesis advances by presenting more three gait analysis tools, i.e., the ability to **decode LMs** (Chapter 5), and to **estimate ankle joint torques** (Chapter 6.3), and **energy expenditure** (Chapter 6.4), in real-time.

3.2.4 HIERARCHICAL CONTROL ARCHITECTURE

The SmartOs system endows a **hierarchical control architecture organized into three levels**, as suggested in the study [9]. Inspired by the human motion control system, this architecture integrates both structural and functional aspects of control and sensor feedback systems. At the high-level, known as the perception layer, the system generates user-oriented trajectories. The mid-level acts as the translation layer, being responsible for transforming the user-oriented trajectories into reference trajectories for the AO in accordance with walking speed. At last, the low-level generates assistive commands, ensuring that the state of the AO effectively tracks the desired assistance trajectory in a timely manner. Currently, the control architecture includes low-level position-based and torque-based tracking controllers using Proportional Integral Derivative (PID) and Feedback-Error Learning (FEL) control, respectively [89].

In terms of control frequency, the high- and mid-level frequencies were set at 100 Hz, a sufficient rate for human-machine gait analysis. Conversely, the low-level operates at 1 kHz to allow high-frequency operation, which is conducive to effective human-machine tracking control loop dynamics. The software routines controlling the low- and mid-level controllers were coded in C and implemented on the STM32F407VGT microcontroller. In contrast, the high-level controllers, coded in C++, are executed within the CCU, which is housed within a UDOO X86. This architectural framework embodies a modular design, facilitating scalability to incorporate additional assistive control strategies as required to expand SmartOs into a versatile robot-based gait training solution.

Currently, the SmartOs system includes seven user-centered, closed-loop assistive control strategies, as presented in Table 3.2. These strategies have been carefully designed to address the therapeutic purposes identified for the SmartOs system in post-stroke gait training. Taken together, these strategies make SmartOs adaptable to different therapeutic approaches and address both immediate and permanent changes in motor ability. Each strategy allows for gait speed adjustments in the range of 0.5 to 1.6 km/h, taking into account the mechanical limitations of the AOs, thereby facilitating gait training across the different challenges inherent in each strategy. This Ph.D. thesis advances by proposing the **AAN LM-driven trajectory** (Chapter 6.2), the **AAN EMG-based** (Chapter 6.3), and the **AAN HITL** (Chapter 6.4) controls.

Table 3.2 – Different control strategies available in the SmartOs system

Control Strategy	Therapeutic Purpose	Benefits
Zero-torque Control	Rehabilitation	➤ Familiarization period ➤ Muscle strengthening
Trajectory-tracking Position Control	Assistance and/or Rehabilitation	➤ User-oriented repetitive gait training ➤ Recovery of the user's gait pattern (range of motion (ROM) and symmetry)
Adaptive Impedance Control	Rehabilitation	➤ Recovery of the user's gait pattern (ROM and symmetry) ➤ Invoke the user's active participation ➤ Muscle strengthening ➤ Manual assistance level adjustment ➤ Long-term recovery of functional motor abilities
EMG-based Control	Rehabilitation	➤ Invoke the user's active participation ➤ Muscle strengthening ➤ Long-term recovery of functional motor abilities
AAN LM-driven Trajectory Control	Assistance and/or Rehabilitation	➤ User-oriented repetitive gait training in different LMs ➤ Invoke the user's active participation
AAN EMG-based Control	Rehabilitation	➤ Recovery of the user's gait pattern (ROM and symmetry) ➤ Invoke the user's active participation ➤ Muscle strengthening ➤ Automatic assistance level adjustment ➤ Long-term recovery of functional motor abilities
AAN HITL Control	Assistance	➤ Energetic-efficient motor recovery

3.2.5 GRAPHICAL APPLICATION

The **mobile graphical application** facilitates the intuitive configuration of all SmartOs modules, allowing the system to be set up for monitoring and/or assistance in training sessions. This application meets requirements such as (i) simplified and guided interaction for fast, natural, and easy navigation, and (ii) the use of explicit graphical components for better user understanding, as initially defined in the study [2]. Developed for the Android operating system, all messages are transmitted via the Bluetooth

protocol to the SmartOs CCU. In this Ph.D. thesis, the mobile graphical application has been extended to allow the selection of **new sensors** (MuscLab, and EMG Trigno Avanti system), **algorithms** (ankle joint torque estimation, LM decoding, and energy expenditure estimation), and **control strategies** (AAN LM-driven trajectory, AAN EMG-based, and AAN HITL controls), as shown in Figure 3.3.

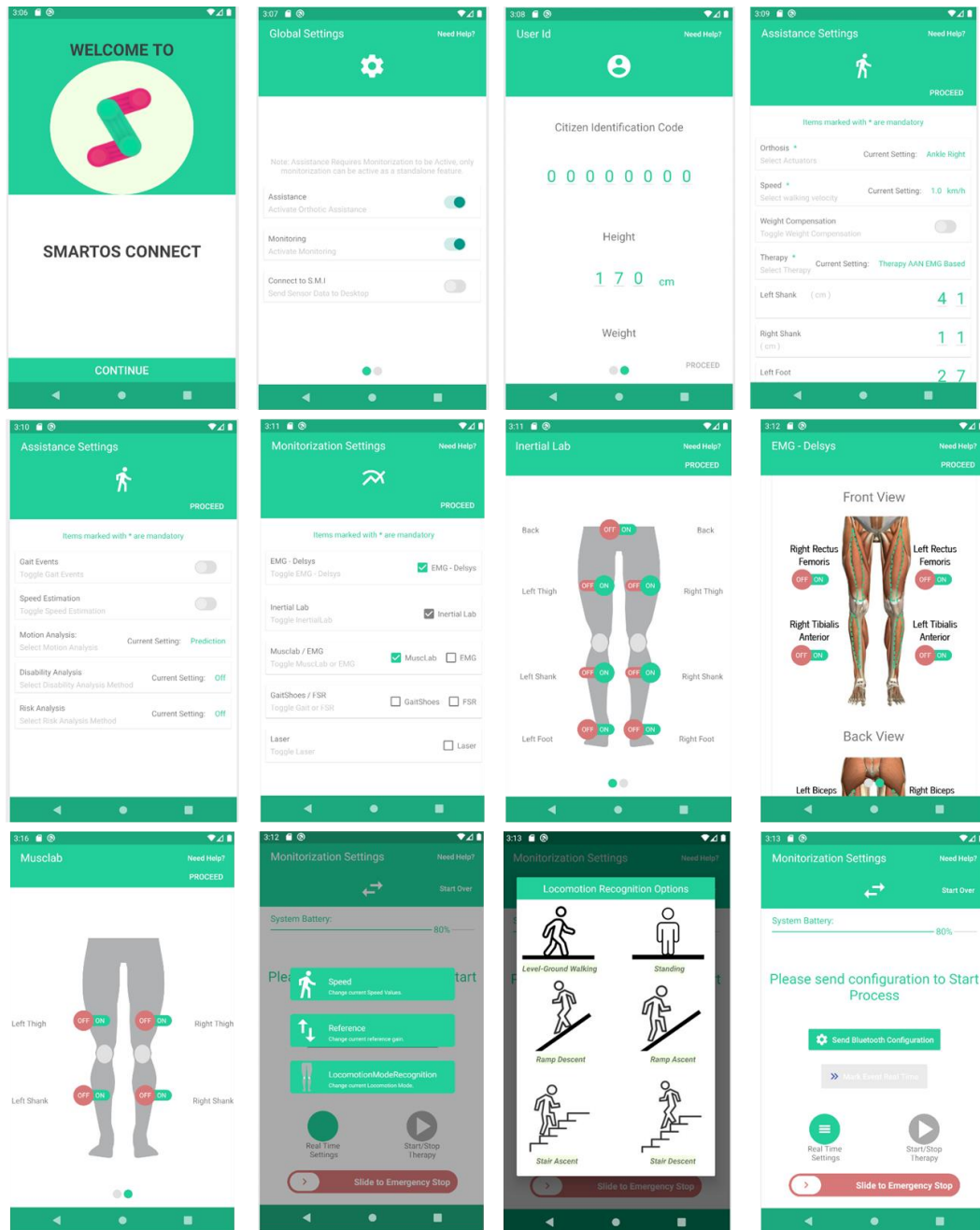


Figure 3.3 – Mobile graphical application.

3.3 CONCLUSIONS

For delivering personalized and user-oriented assistance for post-stroke patients, the modular and hierarchical architecture of the SmartOs system was extended. The **MuscLab system (Chapter 4)** was developed and integrated into the SmartOs system to enable the **monitorization of multiple lower limb muscles simultaneously**, in real-time. Future research on this sensor may allow (i) muscle fatigue estimation; (ii) LMs decoding; and (iii) lower limb joint and segment angle estimation.

Additionally, the integration of an **LM decoding tool (Chapter 5)** and the development of an **AAN LM-driven trajectory control (Chapter 6.2)** enables the adaptation of the system dynamics according to the user's locomotion intentions.

The integration of the **EMG Trigno Avanti system** and the development of a **joint torque estimation algorithm** facilitated the design of an **AAN EMG-based control strategy (Chapter 6.3)** to assist the user as much and when needed.

Finally, the development of **AAN HITL control (Chapter 6.4)**, based on real-time estimation of energy expenditure, makes it possible to optimize the control parameters of the AOs to help users reduce their metabolic costs.

The mobile graphical application was updated with these new functionalities to enable the application of these strategies during rehabilitation therapies.

4. MUSCLAB SYSTEM

This chapter describes the MuscLab system, an **elastic and flexible textile band** that simultaneously **monitors muscle contraction** in extensor and flexor muscles and the kinematics of the segment in which it is located. The chapter begins with an introductory overview of the MuscLab system, followed by the conceptual design and functionalities of the system. In addition, this chapter presents the technological solutions implemented, taking into account the hardware and software interfaces. The chapter ends with the system validation against gold-standard tracking technologies.

4.1 INTRODUCTORY INSIGHT

According to the World Health Organization, **musculoskeletal disorders (MSDs) are the world's leading cause of human motor disability**. An estimated 1.71 billion people worldwide live with MSDs. Most MSDs are associated with the work context, sedentary lifestyle, and practice of sports, at a professional or amateur level [90]. As in the case of stroke, MSDs make it difficult to carry out daily tasks at home and work and are the **main reason for absenteeism and early retirement** [91]. This raises the need for developing **solutions to promote objective, non-invasive, and real-time monitoring of muscle contraction and relaxation**. Ideally, this solution should be versatile to use in different contexts, such as (i) **health**, to support the clinical diagnosis of the evolution of muscle contraction or to serve as a tool for gait disability level assessment in post-stroke patients; (ii) **sports**, for analysis of muscle performance and prediction of the risk of MSDs; (iii) **work**, to support the ergonomics assessment of muscle condition and prediction of the risk of MSDs.

Typically, surface muscle contraction monitoring is conducted by expensive but high-precision sensing EMG equipment. The gold-standard surface EMG solutions include the non-invasive EMG electrodes from Ultium EMG (Noraxon, Toronto, Canada) [92] and Pico EMG (Cometa Systems, Newburg, USA) [93], or the dry EMG sensors such as Trigno Avanti (Delsys Incorporated, Natick, USA) [87]. However, the long-term use of these sensors can be affected by (i) sweating; (ii) temperature variations; and, (iii) movements between the skin and the electrodes [42]. Furthermore, if several agonist and antagonist muscles need to be monitored simultaneously, it will need as many sensors as the number of muscles to monitor. This may result in a more intrusive and time-consuming solution for donning and doffing, narrowing its practical use.

Current challenges center on the development of easily wearable and cost-effective sensors that enable the real-time monitoring of several muscles simultaneously in a practical way. In this connection, this chapter presents a second version of the MuscLab system (advancing [94]), which corresponds to a

low-cost, non-intrusive, self-calibrated, and stand-alone prototype to monitor the muscle contraction in several muscles of a human body segment, simultaneously.

4.2 CRITICAL ANALYSIS OF RELATED WORK

Different devices have been proposed for the non-invasive evaluation of muscle contraction. The studies [95], [96] proposed the development of **garments covered with dry EMG electrodes**. In the study [95], two garments (trousers and a shirt) monitored the electrical activity of the muscles present in the lower limbs, upper limbs, and torso, making a maximum of 19 muscles. In the study [96], a flexible and elastic textile band with three electrodes sewn parallel to each other was responsible for measuring EMG signals in fingers, wrists, elbows, shoulders, back, hips, knees, ankles, and neck. Considering the two patent documents presented above [95], [96], it was verified that the inclusion of EMG electrodes in textiles with flexible character facilitates the monitoring of several muscle groups simultaneously. Nonetheless, **dry EMG electrodes need to be always in contact with the user's skin**.

As an alternative to overcome the limitations of using EMG, **MMG** has emerged for muscular analysis [97]–[103]. MMG sensors, although they do not measure electrical signals from muscles, can detect whether muscles are contracting or relaxing, **without the need to be in direct contact with the user's skin**. The principle underlying the MMG sensors is that muscle contraction is typically associated with muscle shortening, causing an increase in muscle cross-sectional area, stiffness, tension, and mechanical vibration. In this connection, an MMG sensor (e.g., force, capacitive, and inertial sensor) positioned above the muscle may detect its contraction [97].

The studies [97], [98] used a **piezoresistive force sensor** placed on arm muscles to monitor their contraction. Due to its piezoresistive property, there is a shape variation of the force sensor as the muscle under the sensor is contracted; thus, varying the sensor resistance. Both studies verified that the MMG signals have a similar pattern to the envelopes of the EMG signals. Moreover, a patent document [99] described another MMG-based device for monitoring muscle activity, capturing muscle mechanical vibrations through an **inertial sensor**. The patent document [100] used a **capacitive sensor** over the muscle to measure capacitance variations according to muscle contraction and relaxation. From these studies [97], [98] and patent documents [99], [100], it was found that the use of force, inertial, and capacitive sensors allows the monitoring of muscle activity of the muscles where the sensors are located. However, these solutions may become non-practical for daily use when it is necessary to monitor multi-

muscle groups of a body segment simultaneously since **the number of MMG sensors increases according to the number of muscles to monitor**.

Studies [101], [102], [103] proposed a device that can monitor the muscle contraction of several muscles or muscle groups simultaneously. The study [101] presented a **cord-shaped sensor with piezoresistive properties** to measure muscle contraction in the forearm muscles. To do this, the cord was placed around the forearm segment. The contraction of agonist and antagonist muscles changes the length of the cord; thus, varying its resistance. Despite simultaneously monitoring the contraction of agonist and antagonist muscles, **this solution cannot discriminate contractions of both muscles**, since both contractions cause an increase in the length of the cord.

On the other hand, the study [102] disclosed a **flexible textile band** (72% nylon and 28% spandex) for monitoring the muscle contraction of the muscles in the shank segment, while discriminating which muscle is contracted. A **flexible, piezoresistive, and e-textile (conductive textile)** has been integrated into an external textile band and sewn into a matrix shape. The external textile band was designed for the shank segment and, due to its matrix configuration, it is possible to discriminate which muscles of the shank region are contracted/relaxed through the pressure they make on the different zones of the matrix. Similarly, in the patent document [103], a **circular band with pressure sensors** is described for the simultaneous monitoring of muscle contraction/relaxation of muscles responsible for hand, wrist, or arm movements. Although these two approaches [102], [103] can monitor the muscle activity of several muscles simultaneously, the **textile bands do not have elastic characteristics**. As such, these solutions require the development of a user-specific monitoring device to ensure the proper sensor placement according to the user's anthropometry.

Considering all the studies and patent documents presented above, it becomes imperative to develop a solution based on MMG sensors sewn onto a flexible and elastic textile band, so that the same device can be used for different anthropometries and on different parts of the human body. For this purpose, this Ph.D. thesis advances with the **MuscLab system – a stand-alone MMG solution based on e-textile (piezoresistive textile) sensors sewn onto a flexible and elastic textile band**. The MuscLab system was designed as a proof of concept to simultaneously monitor and discriminate the muscle contraction of the shank segment muscles (mainly, the *tibialis anterior* and *gastrocnemius lateralis*) in individuals with different anthropometries.

4.3 METHODOLOGY

All the steps followed in designing the MuscLab system are presented in this section. The section starts with the system requirements, followed by the system overview presenting all the specifications. The section proceeds with a deep insight into the hardware and software features presented by the MuscLab, ending with the presentation of the protocol adopted to validate the proposed system.

4.3.1 REQUIREMENTS

The MuscLab system was designed through a **user-centered approach**, including features that favor its acceptance. To this end, as main requirements, the system should (i) be a **stand-alone** monitoring solution, incorporating the sensing, processing, transmitting, and power supply units into a single, compact, and non-intrusive device; and (ii) use a **wireless protocol** to transmit data to external units, avoiding wired communication means to be easy-to-use. Additionally, the system must be (i) **flexible**, to accommodate different human movements without break; and (ii) **elastic**, presenting the ability to adapt to different anthropometries by stretching and returning to its original shape as a response to muscle contraction and relaxation, respectively. Moreover, the system should integrate (i) an **IMU sensor** to analyze the kinematics of the segment where the MuscLab system is positioned; and (ii) a **piezoresistive textile sensor** to monitor muscle contraction/relaxation. Table 4.1 presents the functional and non-functional requirements set for developing the MuscLab system.

Table 4.1 – MuscLab requirements

Requirement	Value
Real-time data acquisition	100 Hz
Wireless data transmission	Bluetooth > 4.0
Low packet loss	< 5%
Synchronization with third-party systems	-
Rechargeable battery	Autonomy: > 2h
Built-in inertial sensor	Accelerometer ($\pm 16G$ full scale) and gyroscope (± 2000 °/s)
The electric circuit must be isolated from the user	Inner band
The electric circuit must be protected against possible external perturbations	-

Requirement	Value
The electric circuit must be coupled inside a small and compact case	Length: < 5.5 cm; Width: < 4.5 cm; Height: < 2.5 cm
Low mass	< 100 g
The textile band must be flexible, elastic, and adjustable to different anthropometries	35 cm < Shank perimeter < 45 cm*
Easy preparation	Donning and Doffing: < 2 minutes
The system must not limit the user's movement	-

*These shank perimeters were chosen since they correspond to the values typically presented by adults with the body mass permitted to use the SmartOs system (50 - 100 kg).

4.3.2 SYSTEM OVERVIEW

MuscLAB consists of a flexible and elastic textile band (47% recycled polyamide, 25% non-recycled polyamide, and 28% elastane) with a double layer: an inner layer and an outer layer, as depicted in Figure 4.1. The inner layer (Figure 4.1-3) is instrumented with **piezoresistive textile strips** (Figure 4.1-8) to assess muscle contraction and it ensures that the piezoresistive textile sensors do not contact with the user's skin. The outer layer (Figure 4.1-4) guarantees the sensors' isolation from the environment. Both inner and outer layers are elasticated to facilitate adaptation to different anthropometries. These bands integrate a Velcro fastener (Figure 4.1-6) to facilitate donning and doffing by the user.

Additionally, the electronic board (Figure 4.1-5), which powers the entire system and acquires, processes, and transmits the sensor data to an external unit, is coupled in a **3D printed case** that is placed over the Velcro area. The connection between the piezoresistive textile sensors and the electronic board is established by conductive wires with elastic properties to meet elasticity requirements (Figure 4.1-7). The system also presents an inertial sensor that is embedded in the electronic board.

The external unit, hereafter defined as the CCU (Figure 4.1-9), runs the **MuscLab Application**, which is responsible for receiving data from the MuscLab system via the **Bluetooth communication** protocol at 100 Hz.

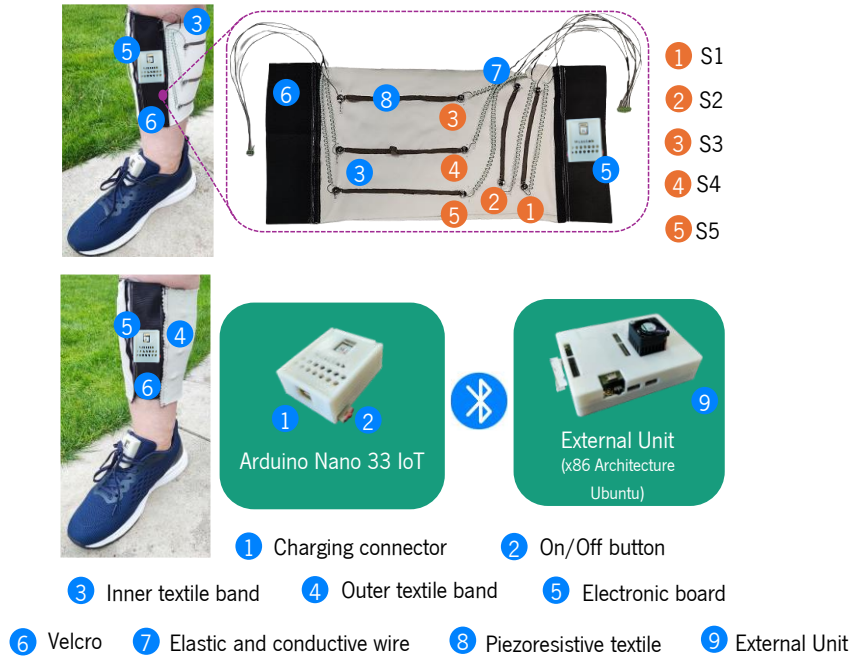


Figure 4.1 – MuscLab system overview. S1, S2, S3, S4, and S5 represent each one of the five piezoresistive textile strips, respectively.

4.3.3 HARDWARE

At the hardware level, MuscLab comprises three physical units: (i) **control unit**; (ii) **sensor unit**; and (iii) **power supply unit**, as depicted in Figure 4.2.

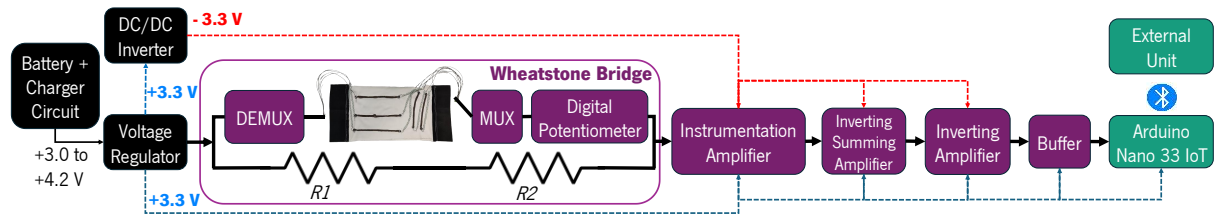


Figure 4.2 – MuscLab hardware diagram. The black, purple, and green boxes represent the power supply, sensor, and control units, respectively. $R1$ and $R2$ are fixed resistances of the Wheatstone bridge with a value of 510Ω each.

A. Control Unit

The **control unit** includes (i) an **Arduino Nano 33 IoT** embedded in the electronic board (Figure 4.1-5); and (ii) an **external unit**, positioned in the same environment as a data collection is conducted. A wireless communication protocol with 4.2 technology (Bluetooth 4.2) was employed to establish the communication between the Arduino Nano 33 IoT and the external unit. With respect

to the Arduino Nano 33 IoT, it comprehends two individually programmed processors: (i) Cortex-M0 32-bit SAMD21, responsible for acquiring data from the sensors (inertial and piezoresistive textile sensors), calibrating the sensors' data, monitoring the battery level, and generating packets to send the sensor data to the external unit; and (ii) u-blox NINA-W102, responsible for handling the Bluetooth 4.2 communication with the external unit.

The external unit corresponds to an external platform running the Ubuntu operating system. It must contain a processor and random-access memory of at least 2.24 GHz and 4 GB, respectively. In this case, the UDOO x86 was employed. The external unit is responsible for (i) receiving data from the inertial sensor, the piezoresistive textile, and the system's battery level; (ii) filtering the piezoresistive textile sensor data; (iii) storing all data in physical memory; and (iv) quantifying muscle contraction.

B. Sensor Unit

The **sensor unit** includes an **inertial sensor** (integrated into the control board - Arduino Nano 33 IoT) and the **e-textile**, a configurable sensor made up of piezoresistive textile strips.

The inertial sensor (LSM6DS3) contains an accelerometer (± 16 G full scale) and a gyroscope (± 2000 °/s). It monitors three-dimensional angular velocity and linear acceleration of the limb where is placed on. Since this sensor is already integrated into the Arduino Nano 33 IoT, it sends data through the I₂C protocol.

The piezoresistive textile sensor consists of a flexible, elastic, and conductive fabric (i.e., e-textile sensor) with piezoresistive properties made of 78% polyamide and 22% elastane with a 99% pure silver bath: **Shieldex® Technik-tex P130+B**. This piezoresistive textile sensor was selected given its proper performance from a comparison of sixteen piezoresistive textiles presented in the study [104]. It showed (i) no signs of fatigue during stretching; (ii) the quickest responses between relaxing and stretching movements; (iii) better elasticity and stability when relaxed; (iv) the best linearity; and (v) low hysteresis (< 17%) [104]. Nonetheless, it is important to note that, according to the study [104], the chosen piezoresistive textile showed signs of relaxation fatigue after 75 relaxation cycles.

As a proof of concept to monitor the muscular activity of the shank segment muscles (mainly, the *tibialis anterior* and *gastrocnemius* muscles), a specific configuration composed of five piezoresistive textile strips was employed, as depicted in Figure 4.3. To this end, **two strips were arranged diagonally at the shank front (S1, S2)** and **three strips were arranged**

horizontally at the shank back (S3, S4, S5), all placed transversely to the direction of expansion of the mentioned muscles. This configuration makes it possible to (i) determine the location of the muscle group that is contracted/relaxed (flexor or extensor groups); (ii) determine when the contraction/relaxation occurs; and (iii) quantify the contraction exerted by each muscle group.

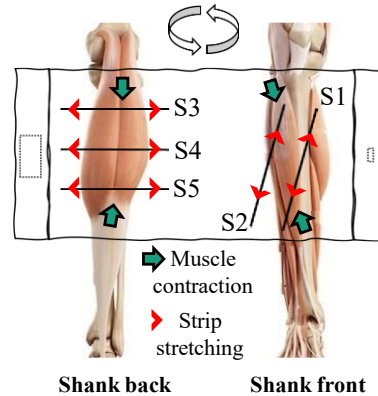


Figure 4.3 – Arrangement of S3, S4, and S5 in the shank back and S1 and S2 in the shank front.

Considering that the Shieldex® Technik-tex P130+B presents a small working range (from 56.4 to 62.7 Ω [104]), an additional electronic setup was designed to detect small resistance variations and to linearize the measured signals. For that, the piezoresistive textile strips were incorporated into a Wheatstone bridge together with a digital potentiometer (AD8400 1 k Ω), as depicted in Figure 4.2. A single Wheatstone bridge was used, which interacts with each strip through an 8-channel demultiplexer/multiplexer (74HC4051), reducing the dimensionality of the electronics. The left bridge is composed of two resistances with a fixed value of 510 Ω each. The right bridge presents the demultiplexer, the piezoresistive textile strips, the multiplexer, and the digital potentiometer (Figure 4.2).

The resistance variation in each strip was detected by an instrumentation amplifier (INA818) with a unitary gain. Then, an inverting summing amplifier was employed to add gain to the signal and an empirical offset of 0.75 V. The offset summing was done to ensure that there were no negative values before reading the signal through the 12-bit Analog-to-Digital Converter (ADC) of the Arduino Nano 33 IoT. As the different strips can capture different levels of muscle contraction, different gain settings were required for each strip. To this end, the inverting summing amplifier incorporates another digital potentiometer (AD8400 50 k Ω). This enables the automatic adjustment of the gain per strip. After, an inverting amplifier with a gain of 2 was employed to obtain positive voltage values. At last, a rail-to-rail buffer powered between 0.0 and 3.3 V was used to prevent the ADC from damages related to possible negative voltages or voltages higher than the admissible value by the ADC, i.e.,

3.3 V. All these surface mount device components were soldered onto a printed circuit board, together with the Arduino Nano 33 IoT and were coupled inside a 3D printed case, depicted in Figure 4.1-5.

The communication between the electronics and the piezoresistive textile strips takes place via a flexible, elastic, and conductive thread (Condustretch 5 ISO Ci-0.48 P2) composed of wires organized in a zigzag pattern (Figure 4.1-7). By organizing these wires in a zigzag pattern, it is possible to maintain the desired elasticity, with a stretch capacity of 150%. This conductive thread was chosen for three purposes. First, it presents a resistance equal to or less than $2.5 \Omega/\text{m}$, a value that remains invariable when the thread is stretched. Second, it is an insulated conductor wire, protecting it against possible external interference. Third, the elastic properties of the conductive wires meet elasticity requirements.

C. Power Supply Unit

The **power supply unit** includes a **3.7V 450 mAh rechargeable LiPo battery** (voltage ranging from 4.2 V to 3.1 V). This unit also integrates a voltage regulator that ensures a stable voltage of 3.3 V, regardless of the battery voltage variation. A DC/DC inverter was introduced at the output of the voltage regulator to generate -3.3 V. While the 3.3 V voltage is used to power the Arduino Nano 33 IoT and as the positive voltage supply for all the integrated circuits, the -3.3 V voltage is used as the negative voltage supply for the integrated circuits. Additionally, this unit presents an On/Off button to turn on/off the system (Figure 4.1-2). The battery is charged through a battery charger (BQ24091DGQR) via a micro-USB connector (Figure 4.1-1) when connected to a 5V charger via USB.

4.3.4 SOFTWARE

At the software level, two algorithms programmed in C++ code were developed: **an Arduino code** implemented on the Arduino Nano 33 IoT, and a **MuscLab Application Programming Interface (API)** implemented on the UDOO x86. These two algorithms were programmed to communicate with each other through Bluetooth 4.2.

Figure 4.4 depicts the flow diagram between the Arduino code and the API. After switching on, the system performs a first calibration, adjusting the resistance of the digital potentiometer (AD8400 1 k Ω) on the Wheatstone bridge automatically. This calibration aims to balance the Wheatstone bridge. Since an offset voltage of 0.75 V was implemented in the hardware, the Wheatstone bridge is balanced when the voltage read by the ADC of the Arduino Nano 33 IoT is close to this offset voltage (0.75 V). To do this, a software routine was implemented to adjust the resistance of the digital potentiometer according to the

resistance of each piezoresistive textile strip. During this calibration step, the user must remain in a sitting position (with the knee joints performing 90°) and static for 10 seconds, while the software routine finds the optimal position among 256 possible programmable positions of the digital potentiometer until the output of the ADC reaches 0.75 V for each piezoresistive textile strip.

Once calibrated, the algorithm moves on to a calibration routine for the second digital potentiometer (AD8400 50 kΩ). This potentiometer is responsible for amplifying the signal read for each strip, allowing gains between 1 and 250. To calibrate it, the user was asked to perform dynamic contractions (maximum voluntary contractions are also valid) for 10 seconds. This calibration aimed to determine the gain necessary to ensure that the maximum voltage is 3.3 V, the maximum value allowed by the Arduino.

After calibrating the digital potentiometers, the Arduino's program waits to receive a command message from the MuscLab API. These commands are received by the Nina processor and sent via UART serial communication to the Cortex-M0 32-bit SAMD21 of the Arduino Nano 33 IoT. If the command sent by the API is a start command, it will initiate the collection of inertial data, piezoresistive textile data, and battery voltage level. This is done by reading the battery data every 5 minutes and the inertial and piezoresistive data every 10 ms. The data are sent to the MuscLab API at 100 Hz through a data message, organized as follows:

- 1 byte to indicate the start or header of the packet (indicated with the value of the 'h' character);
- 1 byte comprising the message number and the battery value (first 4 bits for the message number, 0 to 15; and the last 4 bits for the battery value, (0, 10, 20, ..., 100 %) divided by 10;
- The sensor data bytes (variable size according to the number of sensors requested by the API, these can be inertial data and/or data from the piezoresistive textile);
 - Inertial sensor: 2 bytes per signal (accelerometer and gyroscope in X, Y, and Z components) - a total of 12 bytes;
 - Piezoresistive textile sensor: 2 bytes per strip - a total of 10 bytes.
- 2 bytes indicating the end of the packet or the tail of the packet (indicated with the value of the 't' character).

Once the data has been received by the API, the data are parsed into package ID, battery level, time stamp, 3-axis accelerometer and gyroscope, and voltage read of each piezoresistive textile strip. The piezoresistive data is filtered in the API by using a low-pass exponential filter with a cutoff frequency of 5

Hz. The API then saves all data into a text file. The code is continuously running until the user stops it through a stop command sent by the API.

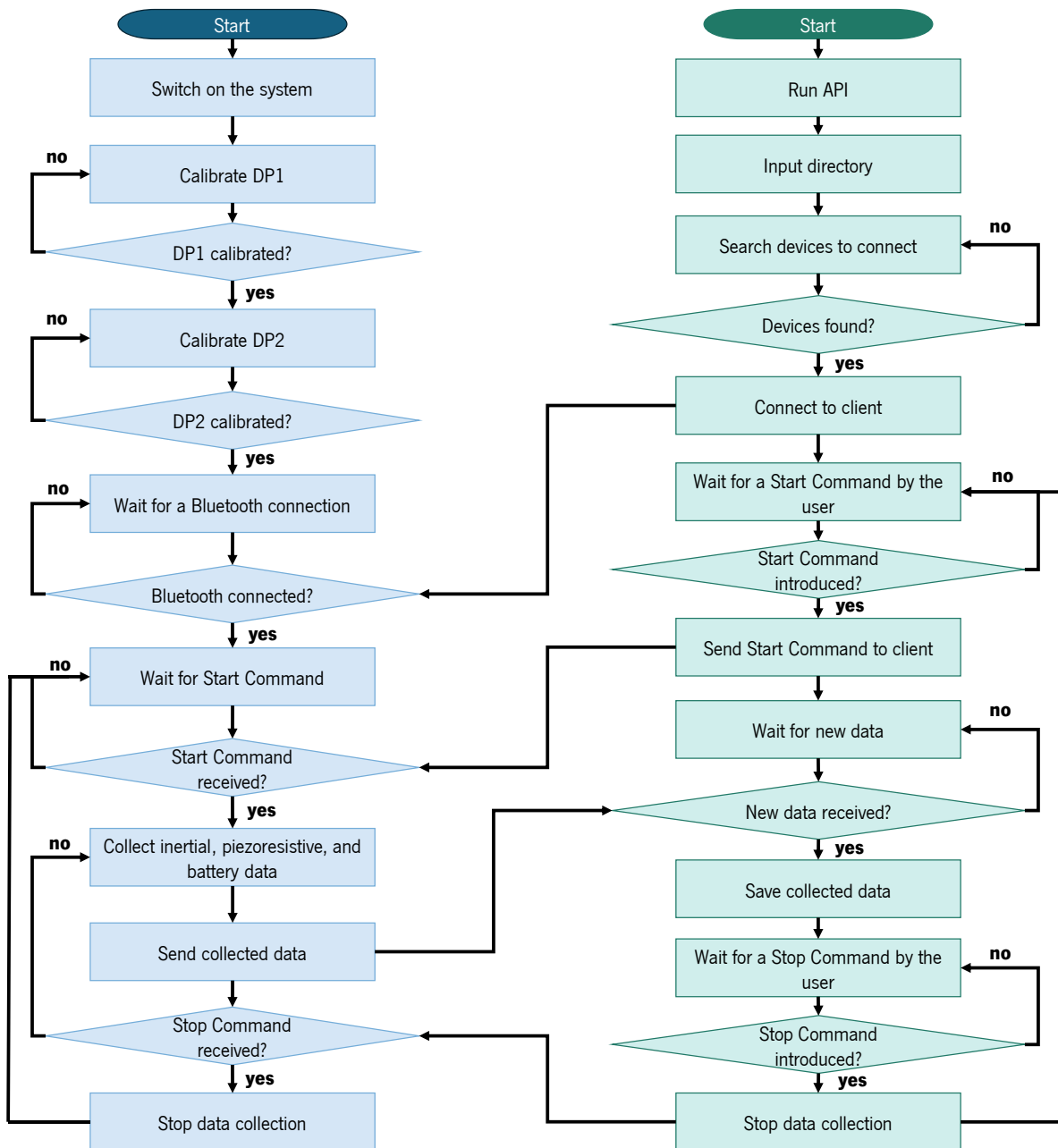


Figure 4.4 – Flowchart of the MuscLab acquisition system. *DP1* and *DP2* represent the Digital Potentiometer of the Wheatstone bridge and summing inverting amplifier, respectively. The blue and green blocks represent the flow diagram of the Arduino and API codes, respectively.

4.3.5 EXPERIMENTAL VALIDATION

Two experimental tests were carried out to infer the operability of the MuscLab system. First, **bench tests** were conducted to check if the requirements defined for MuscLab were met. Moreover, **human tests** were performed to evaluate the reliability of the MuscLab signals against EMG and kinematic signals during dorsiflexion and plantar flexion movements of the ankle joint.

A. Bench Tests

A benching protocol was carried out to evaluate the MuscLab system requirements, stated in Table 4.1, regarding the (i) **acquisition frequency** (100 Hz); (ii) **percentage of packet loss** of wireless communication (below 5%); and (iii) **autonomy** (> 2h). The **MuscLab mass and dimensions** were also measured. The protocol consisted of two trials, where the MuscLab system acquired and transmitted the inertial and piezoresistive textile data at 100 Hz. The protocol started with a battery level of 100%. The battery level was measured with a multimeter at the beginning of the protocol and in 20-minute intervals until the system switched off due to lack of battery power. During the data collection, the time stamp of each received sample at the API was registered. The trial duration was recorded by a chronometer to compute the battery autonomy.

After the data collection, the time between consecutive samples was computed. To infer the acquisition frequency, the average time between consecutive samples was determined. Further, all samples received with a time between consecutive samples of less than 9.9 ms or more than 10.1 ms were considered lost samples. The percentage of lost packets was calculated taking into account the received and lost samples.

B. Human tests

Ten healthy participants (5 males and 5 females) were involved in the validation of the MuscLab system (average age of 26.5 ± 2.8 years old, an average body mass of 65.4 ± 11.2 kg, and an average body height of 169.8 ± 10.9 cm). **The lowest and highest shank perimeters measured were 35.0 and 42.1 cm**, respectively, achieving an average value of 37.6 ± 1.9 cm. Prior to the experiments, all participants gave written informed consent in accordance with the ethical guidelines established by the Ethics Committee of the University of Minho (CEICVS 006/2020).

The protocol started by equipping the participants, as illustrated in Figure 4.5. First, the participants were instrumented with the EMG Trigno Avanti sensors [Trigno Avanti (Delsys Incorporated, Natick, USA)] to capture EMG signals from two lower limb muscles: the *tibialis anterior*

and the *gastrocnemius lateralis* of the right leg. The sensors were positioned above the referred muscles, following SENIAM recommendations [105]. Further, the system was configured to compute the RMS of the EMG signals at 100 Hz. Moreover, participants were equipped with 7 IMUs (torso, thighs, shanks, and feet) from the Xsens Awinda system (Movella – Henderson, USA) to collect lower limb joint angles at 100 Hz.



Figure 4.5 – A participant instrumented with the (i) Trigno Avanti and Xsens Awinda systems (top view); (ii) Trigno Avanti, Xsens Awinda, and MuscLab (without outer band) systems (middle view); and (iii) Trigno Avanti, Xsens Awinda, and MuscLab (with outer band) systems (bottom view).

Then, the participants were instrumented with the MuscLab system at the right shank. The MuscLab system was positioned above the sensors from the Trigno Avanti and Xsens Awinda systems, as depicted in Figure 4.5.

Participants were then asked to perform the N-pose +Walk calibration procedure from the Xsens Awinda system. Participants stood in the N-pose for 3 seconds, then walked 5 meters forward and backward in a straight line. Afterward, participants were asked to sit to perform the MuscLab calibration: remain static for 10 seconds and then perform repetitive dorsiflexion and plantar flexion movements for 5 seconds. Once calibrated, participants completed **three independent tests** per each movement type: dorsiflexion and plantar flexion movements. In all tests, the time was controlled by an external researcher.

The **first test** consisted of the following sequence: 1) started in a relaxed position for 5 seconds (Figure 4.6 – a)); 2) carried out five dorsiflexion repetitions (Figure 4.6 – b)) at three cadences imposed by a metronome, with each cadence separated by a 5-second relaxed position. The chosen cadences were 40, 75, and 105 beats/minute, which may correspond to walking speeds of 1.0, 2.5, and 4.0 km/h [106]. This first test aimed to analyze the **system's responsiveness to different motion cadences**. For that, the delay between the MuscLab signals and the signals collected by the Trigno Avanti and Xsens Awinda systems was computed, for each cadence.

The **second test** included two constant dorsiflexion movements for 3 seconds each, separated by a 3-second relaxed position. This test aims to evaluate the **MuscLab's measuring repeatability**. In this test, for both the MuscLab and Trigno Avanti systems, the percentage of the average magnitude variation between the first and the second dorsiflexion movements was computed.

In the **third test**, the participants were instructed to execute three constant dorsiflexion movements for 2 seconds each, at different ankle dorsiflexion angles, i.e., (i) a small dorsiflexion movement; (ii) a dorsiflexion movement at an intermediate position between the relaxed and the maximum positions; and (iii) a maximum dorsiflexion movement. This magnitude test was performed to verify if the system can **discriminate different muscle contraction levels at different ankle joint angles**. In this connection, the Coefficient of Determination (R^2) was computed between the MuscLab and the Xsens Awinda signals.

Subsequently, the participants were asked to perform the same three tests but for plantar flexion movements (Figure 4.6 – c)).

In addition, the correlation of the MuscLab system with the EMG signals of the *tibialis anterior* and *gastrocnemius lateralis* muscles was assessed under the described dorsiflexion and plantar

flexion movements, respectively. For that, the Spearman Correlation coefficient (r) was used to evaluate the strength and direction of the monotonic relationship between MuscLab and EMG signals. A p -value of 0.05 was used to determine whether the observed correlation between the two systems was statistically significant. According to the study [107], the relationship can be categorized as (i) negligible if $0.0 < r < 0.19$; (ii) weak if $0.20 < r < 0.29$; (iii) moderate if $0.30 < r < 0.39$; (iv) strong if $0.40 < r < 0.69$; and (v) very strong if $r \geq 0.7$.



Figure 4.6 – A participant performing a) a relaxed movement; b) a dorsiflexion movement; and c) a plantar flexion movement.

4.4 RESULTS

4.4.1 BENCH TESTS

The MuscLab system showed an average (i) acquisition frequency of 100.0 ± 0.007 Hz ($\cong$ requirement of 100 Hz); (ii) percentage of packet loss of $0.0972 \pm 0.0318\%$ ($< 5\%$); and (iii) battery life of 2 hours and 9 minutes ($> 2h$).

Regarding the MuscLab dimensions, the final length, width, and height of the case containing the electronic board were 5.4 cm (< 5.5 cm), 4.3 cm (< 4.5 cm), and 2.2 cm (< 2.5 cm), respectively. The flexible textile band presented a length and a width of 33.5 cm and 18.0 cm, respectively, allowing the monitoring of shank segments with perimeters ranging from 33.5 to 48.7 cm.

The mass of the case and flexible textile band were 40 g and 49 g, respectively, comprising a total of 89 g (< 100 g).

4.4.2 HUMAN TESTS

The MuscLab system was able to monitor the muscle contraction of individuals with a shank perimeter ranging from 35.0 and 42.1 cm. Table 4.2 presents the results of the MuscLab system's responsiveness to different motion cadences. According to Table 4.2, all MuscLab signals were, on average, (i) delayed regarding the EMG Trigno Avanti signals (135.8 ± 78.0 ms); and (ii) anticipated regarding the Xsens Awinda signals (-36.8 ± 112.2 ms). Moreover, the average delay of the MuscLab signals measured by each strip was consistent across different cadences, since it varied from (i) 135.5 and 136.2 ms, regarding the EMG Trigno Avanti signals; and (ii) 34.5 and 38.8 ms regarding the Xsens Awinda signals.

Table 4.2 – Average delay (standard deviation) between the MuscLab and EMG Delsys signals, and MuscLab and Xsens Awinda signals, in milliseconds, for each motion cadence (40, 70, 105 bpm)

MuscLab Strip	Trigno Avanti System			Xsens Awinda System		
	40 bpm	75 bpm	105 bpm	40 bpm	75 bpm	105 bpm
S1	138.0 (82.3)	125.0 (84.1)	134.0 (73.2)	- 5.0 (128.4)	- 4.5 (127.1)	- 8.5 (121.3)
S2	136.7 (71.6)	124.0 (79.3)	134.0 (94.3)	- 8.0 (121.4)	- 3.5 (126.7)	- 4.0 (122.1)
S3	129.0 (66.2)	134.0 (90.7)	120.0 (93.4)	- 66.1 (72.1)	- 69.4 (83.5)	- 60.0 (89.4)
S4	127.0 (92.5)	128.0 (95.0)	113.0 (93.2)	- 76.7 (90.1)	- 61.1 (104.4)	- 67.8 (90.8)
S5	146.7 (68.0)	170.0 (43.2)	178.3 (43.7)	- 38.0 (118.2)	- 46.7 (167.4)	- 32.0 (120.4)
Average $\pm$ STD*	135.5 (76.1)	136.2 (78.4)	135.9 (79.5)	- 38.8 (106.0)	- 37.0 (121.8)	- 34.5 (108.8)
Total Average $\pm$ STD	135.8 (78.0)			-36.8 (112.2)		

*STD means standard deviation

The results of repeatability tests focus on the comparison of the piezoresistive textile strips number 1 and 2 (S1 and S2, respectively, of Figure 4.1) with *tibialis anterior* signals for dorsiflexion movements. On the other hand, for plantar flexion movements, the piezoresistive textile strips number 3, 4, and 5 (S3,

S4, and S5, respectively, of Figure 4.1) were compared to the *gastrocnemius lateralis* signals. In this context, the *tibialis anterior* EMG, S1, and S2 signals revealed close average variations of muscle contraction between two performed dorsiflexion movements, namely $3.17 \pm 11.7\%$, $2.97 \pm 4.32\%$, and $2.41 \pm 3.77\%$. Moreover, the *gastrocnemius lateralis* EMG, S3, S4, and S5 signals revealed an average variation of $4.88 \pm 13.7\%$, $5.30 \pm 8.98\%$, $3.47 \pm 8.68\%$, and $-20.2 \pm 94.9\%$.

In relation to the magnitude test results, an R^2 of (i) 0.91 ± 0.12 and 0.92 ± 0.08 was found between the dorsiflexion ankle angle and the S1 and S2 strips, respectively; and (ii) 0.92 ± 0.15 , 0.85 ± 0.18 , and 0.69 ± 0.22 was found between the plantar flexion angle and the S3, S4, and S5 strips, respectively.

Furthermore, Table 4.3 presents the r values obtained between the MuscLab and EMG Trigno Avanti signals, per participant. The results presented in Table 4.3 indicated very strong correlations between the MuscLab signals at S1, S2, S3, and S4 strips and EMG Trigno Avanti signals, reporting average r values above 0.78 ± 0.08 (p -value < 0.05). In detail, very strong correlations were achieved between (i) *tibialis anterior* signals and both S1 and S2 signals ($r = 0.78 \pm 0.07$); and (ii) *gastrocnemius lateralis* signals and both S3 and S4 ($r = 0.78 \pm 0.09$ and 0.77 ± 0.07 , respectively). The S5 signals were moderately correlated with the *gastrocnemius lateralis* signals ($r = 0.38 \pm 0.23$). Moreover, low standard deviation values were verified for S1, S2, S3, and S4 (< 0.09), while the S5 presented the highest standard deviation value (0.23).

Additionally, Figure 4.7 depicts the EMG Trigno Avanti, Xsens Awinda, and MuscLab signals for a random participant executing the validation protocol, i.e., responsiveness, repeatability, and magnitude tests.

Table 4.3 – Spearman Correlation coefficient (r) between the MuscLab and EMG systems. A p -value below 0.05 was verified in all correlations

Participant ID	Shank Perimeter (cm)	Shank Length (cm)	r				
			S1	S2	S3	S4	S5
1	42.1	33.0	0.84	0.83	0.80	0.76	0.33
2	38.2	33.0	0.70	0.74	0.77	0.84	0.48
3	38.8	35.8	0.86	0.88	0.58	0.71	0.49
4	37.9	31.5	0.74	0.71	0.66	0.74	0.75
5	35.0	41.5	0.84	0.87	0.87	0.63	0.75
6	36.5	36.4	0.67	0.70	0.81	0.77	0.22

Participant ID	Shank Perimeter (cm)	Shank Length (cm)	<i>r</i>				
			S1	S2	S3	S4	S5
7	37.4	35.0	0.74	0.75	0.79	0.83	0.17
8	37.9	35.0	0.70	0.72	0.81	0.75	0.41
9	35.3	34.4	0.88	0.85	0.89	0.84	0.07
10	37.2	33.2	0.83	0.71	0.77	0.86	0.15
Average ±	37.6 ± 1.9	34.9 ± 2.6	0.78 ±	0.78 ±	0.78 ±	0.77 ±	0.38 ±
STD			0.07	0.07	0.09	0.07	0.23

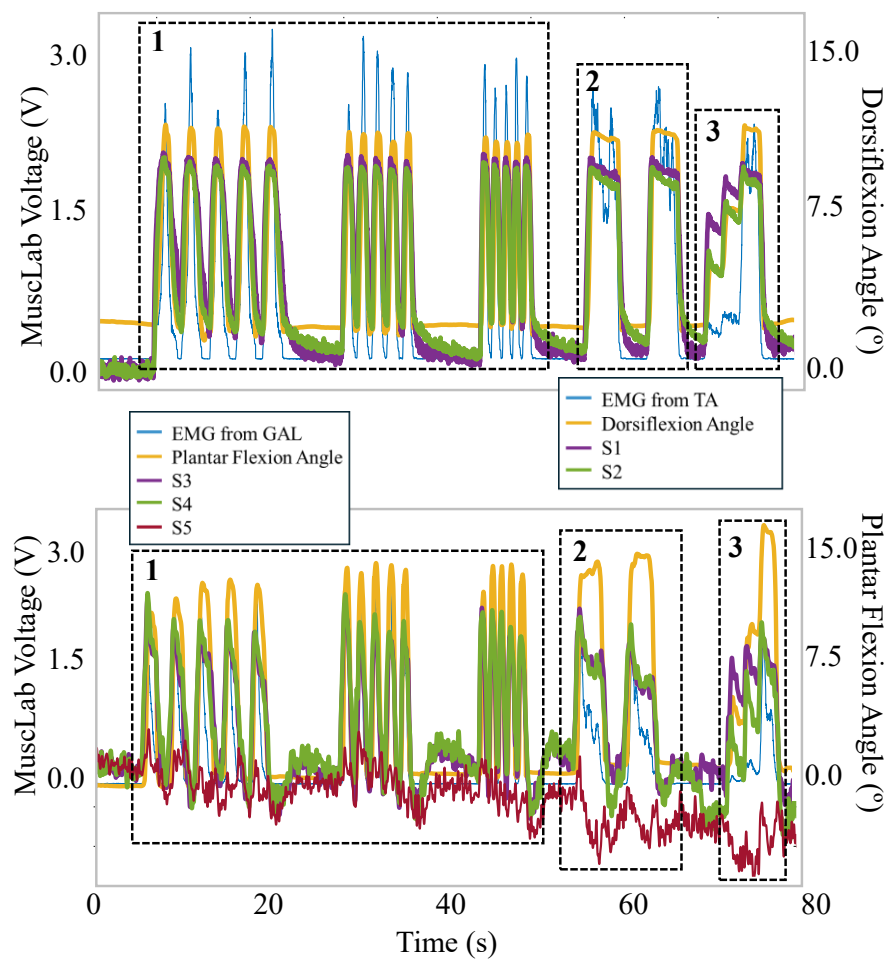


Figure 4.7 – A participant performing dorsiflexion (top view) and plantar flexion (bottom view) movements. Boxes 1, 2, and 3 represent the speed, repeatability, and magnitude tests, respectively. For easier visualization, the magnitude of EMG signals was scaled to MuscLab signal magnitudes using a factor of $\times 10,000$.

4.5 DISCUSSION

This study proposes a flexible and elastic textile band instrumented with piezoresistive textile sensors to monitor the muscle contraction of individuals with different anthropometries. In an attempt to address the state-of-the-art limitations, the proposed system advances (i) studies [95]–[100] by monitoring muscle contraction of different muscle groups, simultaneously; (ii) study [101] by discriminating the muscle contraction of the agonist and antagonist muscles with a single sensor; and (iii) studies [102], [103] by monitoring the muscle contraction of individuals with different anthropometries (ranging from 35.0 to 42.1 cm) due to the elastic nature of the proposed solution.

In terms of responsiveness performance, the **MuscLab signals were delayed regarding EMG signals (average delay of 135.8 ± 78.0 ms)**. According to the study [97], there is a time delay between the onset of EMG and the onset of force generation, defined as the electromechanical delay. This delay typically varies between 9 and 130 ms [108]. Since an MMG, when positioned in a muscle, measures the response of a force generation, its measured signals are expected to be delayed with respect to the EMG signals. In this context, the average delays reported by the MuscLab system (135.8 ± 78.0 ms) are in line with what would be expected because the MuscLab system is an MMG sensor; it, therefore, detects muscle contraction only after the muscle electrical activation (signal measured by EMG).

Conversely, an **average delay of -36.8 ± 112.2 ms was found between the MuscLab and Xsens Awinda signals**. Despite the high standard deviation value, these results suggest that the MuscLab signals may be anticipated regarding ankle joint kinematics. These results may be justified by the fact that muscle contractions occur from 20 to 100 ms before the user's lower limb kinematic motion [108].

Furthermore, results indicated that the **average delay of the MuscLab signals remained consistent across the tested cadences**. These results are aligned with those presented in the study [104] since from a comparison between sixteen e-textiles, the Shieldex® Technik-tex P130+B (used in the MuscLab system) showed the quickest responses between relaxing and stretching movements. Thus, the MuscLab system can be employed to monitor muscle contractions performed at cadences between 40 and 105 bpm.

In addition, **MuscLab demonstrated sensing repeatability** when measuring similar muscle contractions. Considering the repeatability tests, it was found that (i) the variation in the magnitude of the signals measured in strips S1 and S2 ($2.97 \pm 4.32\%$ and $2.41 \pm 3.77\%$.) was, on average, close to the variation in the magnitude of the *tibialis anterior* signals ($3.17 \pm 11.7\%$); and (ii) the variation in the

magnitude of the signals measured in strips S3 and S4 ($5.30 \pm 8.98\%$, $3.47 \pm 8.68\%$) was, on average, close to the variation in the magnitude of the *gastrocnemius lateralis* signals ($4.88 \pm 13.7\%$). These results are supported by the study [104], which concluded that the used e-textile presented the highest stability, linearity, and low hysteresis. However, the variation obtained for the S5 strip ($-20.2 \pm 94.9\%$) was quite different from the variation recorded for the *gastrocnemius lateralis* muscle. **This result may indicate that the S5 strip could benefit from a system redesign.**

Moreover, the results obtained from the magnitude tests indicated a **strong linear relationship** between the Musclab signals at (i) **S1, S2, and ankle joint dorsiflexion movements** (0.92 ± 0.10); and (ii) **S3, S4, and ankle joint plantar flexion movements** (0.89 ± 0.16). The results are in line with those achieved in studies [109], [110], in which the relation between the muscle bulge of the forearm muscles and the wrist joint angles can be explained by linear regression ($0.92 < R^2 < 0.98$).

The MuscLab system revealed **very strong correlations between *tibialis anterior* and both S1 and S2 signals and between *gastrocnemius lateralis* and both S3 and S4** ($r = 0.78 \pm 0.08$). These results are as expected since the cross-sectional area of a muscle increases as it contracts, i.e., it shortens and thickens [111]. As the muscle thickens, the MuscLab strips over the muscle are stretched and muscle contraction is detected. Moreover, the standard deviation of the r values for S1, S2, S3, and S4 was less than 0.09, indicating that the **MuscLab signals were consistently correlated with the EMG Trigno Avanti signals across participants**. On the other hand, moderate correlations between S5 and *gastrocnemius lateralis* signals ($r = 0.38 \pm 0.23$) were found. The higher standard deviation values at S5 suggest that the correlation between S5 and the EMG signals of the *gastrocnemius lateralis* muscle varied more than the remaining piezoresistive textile strips.

The obtained results may justify a redesign of the MuscLab system. Among different individuals and tests, the achieved performances between S1 and S2 with *tibialis anterior* signals were close, which may suggest that the **design of the MuscLab system can be simplified to a single piezoresistive strip to monitor the *tibialis anterior* muscle contraction**. Regarding the S3, S4, and S5 strips, different assumptions need to be made. While in some individuals, the S3 strips revealed higher metrics with the *gastrocnemius lateralis* activity, in other individuals the S3 metrics were overtaken by the S4 metrics. However, it was not found a relation between the achieved correlations for S3 and S4 and the shank perimeter. **Thus, both S3 and S4 strips should remain in the current design of the system.** On the other hand, despite obtaining moderate performances in some tests, the S5 strip does not add any new information about the *gastrocnemius lateralis* contraction. **Thus, S5 can be removed from the MuscLab design.**

4.6 CONCLUSIONS

Overall, the MuscLab system was able to (i) **detect muscle contractions** performed at different motion cadences (from 40 to 105 bpm); (ii) guarantee the **repeatability** of the measured signals, as MuscLab measured similar values for the same muscle force (similar EMG values); and (iii) **distinguish between different levels of muscle contraction** performed at different ankle joint angles. In addition, the **elastic and flexible properties have allowed the system to be used for different movements and user anthropometries** (ranging from 35.0 to 42.1 cm). The benchmarking analysis with commercial systems (Trigno Avanti (Delsys Incorporated, Natick, USA) and Xsens Awinda (Movella – Henderson, USA) shows that the **MuscLab system is effective for monitoring muscle activity, eliminating the need for complex and expensive capture systems**. Considering the achieved results, the MuscLab system was integrated into the SmartOs system (Chapter 3) as a means of monitoring muscle contraction.

Despite offering promising results in monitoring and discriminating muscle contraction of different muscle groups with a single sensor, there is still room for improvements, namely, (i) optimize the sensor design for different parts of the human body; (ii) improve the sensor responsiveness; and (iii) explore the IMU sensor incorporated into the system to infer about joint and segment angles. Exploring a matrix configuration (as reported in the study [102]) with flexible and elastic piezoresistive textiles may be a plausible solution to discriminate muscle contractions in different human segments.

5. LOCOMOTION MODE DECODING TOOL

This chapter highlights the potential of gait analysis tools to detect and predict different user LMs for gait rehabilitation. It also presents the development and validation of an automatic, versatile, and user-independent tool based on DL for the recognition of different daily LMs. For this purpose, different datasets (kinematic and physiologic data) and DL models are used, and the obtained performance is compared. The performance of the best model found is also tested using data from subjects who have suffered a stroke. The chapter ends with a critical analysis of the effectiveness of the developed gait analysis tool and future directions.

5.1 INTRODUCTORY INSIGHT

Individuals with preserved lower limb mobility demonstrate the ability to **adapt their gait patterns for efficient ambulation across various LMs**. As outlined in the study [112], LMs can be classified into **static** and **dynamic tasks**, where static tasks involve sitting (Sit) or St and dynamic tasks encompass **continuous activities** (like LGW, SD, SA, ramp descent (RD), and ramp ascent (RA)) and **discrete activities**, which involve transitions between tasks. However, **individuals with lower limb impairments encounter challenges in executing these motor tasks successfully** [113].

Wearable assistive devices have been equipped with non-intrusive sensor configurations and sophisticated algorithms to **decode LMs**, with a focus on **adjusting the robot's assistance** to help users accomplish their daily mobility tasks. Despite recent advancements, **it is still unclear which is the best fusion of sensor data and algorithm to use for improving LM decoding**.

5.2 CRITICAL ANALYSIS OF RELATED WORK

Despite the high number of literature studies focused on LM decoding, few studies have decoded the LM when using a wearable assistive device [41], [43]–[46], [62], [114]–[117]. Among these studies, **EMG** and **kinematic sensors** have been widely explored to **decode various LMs**.

With respect to EMG signals, studies have employed (i) raw EMG signals [62]; (ii) time-domain features (mean absolute value, RMS, waveform length, slope sign changes, and zero-crossing) [114]; (iii) frequency-domain (mean power frequency, and median frequency); and (iv) time-frequency-domain features [115]. Although the RMS is the most commonly used EMG feature, the use of raw EMG signals from *semitendinosus*, *vastus medialis*, *gastrocnemius medialis*, and *tibialis anterior* with a convolutional neural network (CNN) seems to provide the highest accuracy (ACC) (99.7%) in decoding LMs [62]. Regarding the kinematic sensors, studies have explored lower limb (i) joint angles [41], [117] and (ii)

segment angles [41], [43]–[46], [116]. There is a prevalence for using thigh and shank segment angles to recognize LMs [43]–[46], [116]. These data have been used with (i) Support Vector Machine models [44]; (ii) Finite State Machine models [41]; (iii) Multilayer Feedforward Neural Networks [45], [46]; (iv) fuzzy-logic methods [116]; and (v) a combination of Support Vector Machine and Finite State Machine models [43]. Despite the study [45] reporting the highest ACC (98.4%), **it is still unclear which is the best fusion of sensor data and classification algorithm to use for decoding LMs.**

Additionally, the timing of LM decoding is crucial and it needs further investigation. LM decoding can be categorized into LM recognition and LM prediction. While **recognition** implies that the LM decoding tool **detects the LM when the user is already on it**, **prediction** aims to **detect the LM that the user will enter**. According to the literature, most of the studies focusing on decoding LMs when using a robotic assistive device, recognize the new LM after the user has already entered on it [41], [45], [46], [62], [114]–[117]. Recognition delays typically range from 50.0 to 1897.9 ms after the start of the new LM. This delayed LM recognition combined with the inherent response delay (also known as latency) of the robot's actuator, can lead to undesirable operation of the robotic assistive device and discomfort in human-robot interaction [118], [119]. Therefore, as suggested in [120], **there is a need for an LM decoding tool that is able to predict the LM the user will enter**. This prediction enables the robotic assistive device to timely adjust its assistance by modifying control parameters, such as position, torque, or stiffness [120].

While the reviewed studies demonstrated a notable capability in decoding various LMs, many existing LM decoding tools integrated into wearable assistive devices present several limitations [41], [43]–[46], [62], [114]–[117]. Specifically, these tools (i) lack the ability to decode several LMs simultaneously using a single decoding tool [43]; (ii) exhibit high recognition delays, classifying the LM only after the user has already transitioned to the new LM [41], [45], [46], [62], [114]–[116]; (iii) do not account for the typically slower gait speeds of individuals with lower limb disabilities, since studies addressed self-selected and/or fixed speeds of healthy participants (typically above 2.7 km/h) [41], [43]–[46], [62], [114], [115], [117]; (iv) are not tested in scenarios different to those in which the tool was trained [41], [43]–[46], [62], [114]–[117]; and (v) are not tested in post-stroke patients [41], [43]–[46], [62], [114]–[117].

This Ph.D. thesis addresses the aforementioned challenges by introducing an **automatic DL tool designed to predict both static and dynamic LMs** (including St, LGW, SD, and SA), during the use of a **wearable assistive device** (SmartOs system [66]). The study advances the current state-of-the-art by investigating the **optimal fusion between sensor data and DL algorithms** for decoding LMs

at slow speeds, considering the preferred gait speeds of individuals with lower limb impairments (below 2.7 km/h) [77]. The DL tool was **tested on both healthy participants and a post-stroke stroke patient** (i) in **different scenarios** to assess the robustness of the LM tool to scenario variation; and (ii) in a **range of speeds** (all within the stroke patient's values) to assess the robustness to speed variation. This solution was implemented such that the SmartOs system is able to predict the upcoming LM while achieving ACCs close to 99.7% (the highest ACC identified in the reviewed studies [62]).

5.3 METHODOLOGY

5.3.1 DATA ACQUISITION

To develop the LM decoding tool, data collection was conducted, acquiring EMG and kinematic data from the lower limbs of able-bodied participants performing four LMs (St, LGW, SA, and SD).

A. Participants

The study involved 15 healthy participants (8 males and 7 females) with an average age of 25.0 ± 2.71 years old, an average body mass of 67.9 ± 13.3 kg, and an average body height of 171.0 ± 8.14 cm. All participants provided written and informed consent, considering the University of Minho Ethics Committee that follows the declaration of Helsinki and the Oviedo Convention (CEICVS 006/2020).

B. Instrumentation and Data Collection

The wireless 8-channel surface EMG system [Trigno Avanti (Delsys Incorporated, Natick, USA)] was used to capture EMG signals from eight lower limb muscles: *tibialis anterior*, *gastrocnemius lateralis*, *biceps femoris*, and *rectus femoris* of both lower limbs, as depicted in Figure 5.1, in blue color. The eight EMG sensors were affixed to the skin, following the recommendations of SENIAM [105]. The RMS of EMG signals was acquired at 100 Hz.

Moreover, the participants were instrumented with seven IMUs of the InertialLab system in the torso and lower limb segments (right and left thighs, shanks, and feet), as depicted in Figure 5.1, in green color. This system acquired at 100 Hz the 3D acceleration and angular velocity, the sagittal angle of each segment, and the sagittal joint angles (hips, knees, and ankles). The study [84] details the segment and joint angles computation.

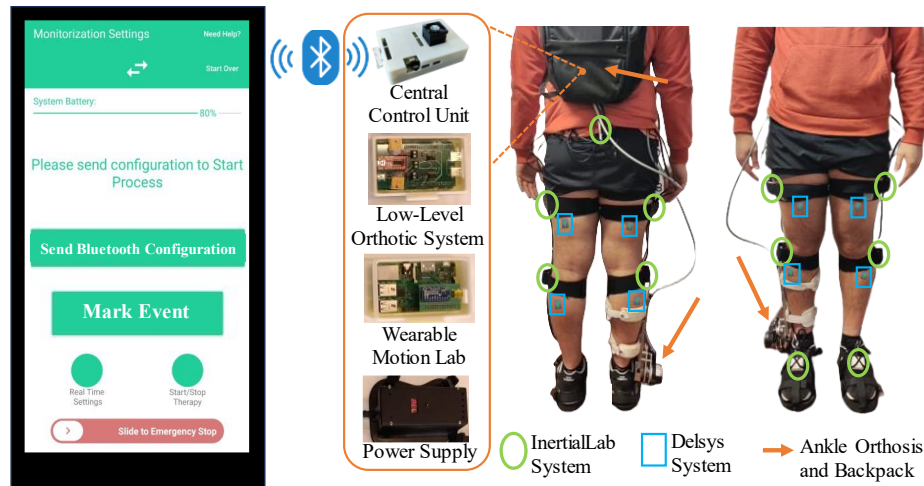


Figure 5.1 – SmartOs' mobile graphical application (left view) and a male participant instrumented with the SmartOs, Trigno Avanti, and InertialLab systems (right view).

C. Experimental Protocol

Once instrumented with the eight EMG and seven IMU sensors, participants performed two Maximum Voluntary Contractions (MVCs) for each muscle to normalize all EMG signals, following the protocol described in the study [121]. Subsequently, participants were equipped with the SmartOs system and provided a 10 min-familiarization session with the device operating under zero-torque control.

The participants then completed a continuous circuit of nine task sequences while the ankle orthosis operated in zero-torque control (Figure 5.2). The sequences, presented in Figure 5.2, consisted of: 1. standing for 10 seconds (St); 2. walking in a straight line for 2.5 meters (LGW); 3. descending stairs with 13 steps (SD); 4. walking again in a straight line for 3.5 meters (LGW); 5. stopping in the standing position for 5 seconds (St); 6. walking in a straight line for 3.5 meters (LGW); 7. ascending stairs with 13 steps (SA); 8. walking in a straight line for an additional 2.5 meters (LGW); and 9. stopping in the standing position for 5 seconds (St). This circuit was repeated five times per participant. During dynamics tasks, participants maintained a fixed cadence dictated by a metronome at 40 bpm. Depending on the participant's height and subsequent step length, this cadence corresponded to gait speeds ranging from 1.0 to 1.5 km/h, as validated in the study [106]. This range of values falls in the slow speeds typically adopted by individuals with motor disabilities [77].

Additionally, all participants were able to perform each transition with the self-selected limb, except in the SD task. At this task, participants were instructed to initiate the SD task with their right foot, making it the leading limb to advance to the next step. Following the advancement with the right

foot, the left foot was then moved to the same step. This SD procedure was followed due to two reasons. First, it aligns with the advice for patients with lower limb impairments to descend stairs with their impaired leg as the leading limb [122]. Second, the ankle orthosis is mechanically limited to a maximum dorsiflexion angle value of 20° (a value easily exceeded when descending stairs with the non-instrumented leg (left leg) being the first to advance).

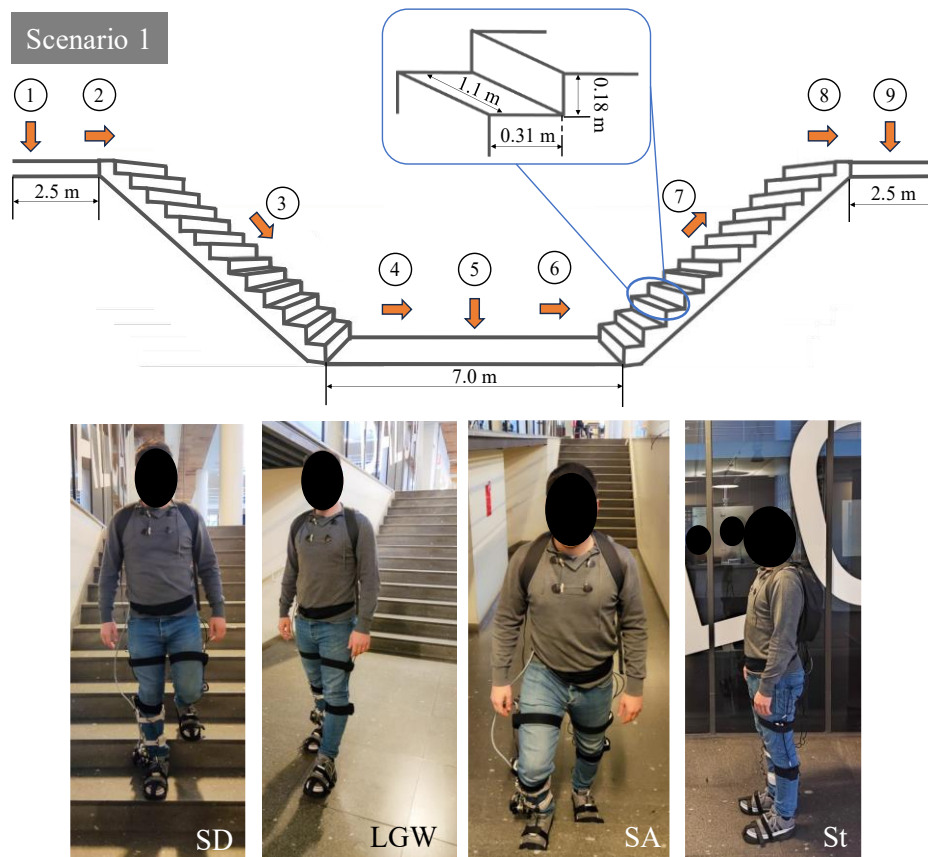


Figure 5.2 – A random male participant performing the four LMs (St, LGW, SD, SA) in the first scenario. Positions (1) and (9) denote the starting and ending positions, respectively.

5.3.2 DATA PREPARATION

During the protocol, a researcher annotated the instant of transitioning between two consecutive LMs. This instant corresponded to a moment between the participant having lifted their leading foot off the ground and the critical moment (the instant when the participant placed the foot on the new LM [44]). This instant was recorded using the SmartOs' mobile graphical application (Figure 5.1) to be synchronous with the remaining collected data. After data collection, all trials underwent manual inspection by two

additional researchers to ensure reliability in labeling the transition instants. At this level, four classes were defined, namely, 0 – St, 1 – LGW, 2 – SD, and 3 – SA.

Considering the reviewed studies [41], [43]–[46], [62], [114]–[117], several types of data were employed in decoding LMs, namely features from EMG signals [114], [115], and segment [43]–[46], [116] and joint angles [41], [117]. There is still no consensus on what type of data yielded more accurate LM decoding. Thus, the LM decoding performance was compared using four types of sensor data: (i) **RMS EMG normalized by MVC** (one of the most used EMG features [114], [115]); (ii) the **segment angles** (torso, thighs, shanks, and/or feet) and their first and second-order derivatives, corresponding to the angular velocity and angular acceleration; (iii) the **lower limb joint angles** (hips, knees, and/or ankles), and their first and second-order derivatives; and, (iv) the **magnitude of 3D acceleration and angular velocity** of the torso, thigh, shank, and/or foot segments. In the segment or joint angle data types, their first and second-order derivatives were computed, since these variables improved the model's performance in empirical tests. The fourth data type aims to explore the potential of directly using IMUs' data, which was not yet explored in the state-of-the-art for LM decoding. Equation 5.1 presents an example of computing the magnitude of 3D acceleration data ($\|a\|$), in which a_x , a_y , a_z represent the acceleration measured in the x-axis, y-axis, and z-axis, respectively.

$$\|a\| = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (5.1)$$

Overall, a total of **38 input combinations** were created and compared. They are identified by an ID in Table 5.1. The data was organized into sequences made up of X columns and Y rows. While X represents the number of samples organized sequentially by time and participants, the Y rows represent the number of inputs.

Table 5.1 – Identification of the type of data used to decode LMs. The joint angles, magnitude of 3D raw accelerometer and gyroscope, segment angles, and EMG data are shaded in green, yellow, gray, and red, respectively

ID	Inputs	ID	Inputs
1	Ankles JAD*	20	MAG (pelvis and thighs)
2	Hips JAD	21	MAG (pelvis)
3	Ankles and hips JAD	22	Feet SAD***
4	Knees JAD	23	Feet and shanks SAD
5	Ankles and knees JAD	24	Shanks SAD
6	Knees and hips JAD	25	Feet and thighs SAD
7	Ankles, knees, and hips JAD	26	Shanks and thighs SAD

ID	Inputs		ID	Inputs
8	MAG** (feet)		27	Thighs SAD
9	MAG (feet and shanks)		28	Pelvis and feet SAD
10	MAG (shank)		29	Pelvis, shanks, and feet SAD
11	MAG (feet and thighs)		30	Pelvis and shanks SAD
12	MAG (shanks and thighs)		31	Pelvis, thighs, and feet SAD
13	MAG (thighs)		32	Pelvis, thighs, shanks, and feet SAD
14	MAG (pelvis and feet)		33	Pelvis, thighs, and shanks SAD
15	MAG (pelvis, shanks, and feet)		34	Pelvis and thighs SAD
16	MAG (pelvis and shanks)		35	Pelvis SAD
17	MAG (pelvis, thighs, and feet)		36	EMG (TA, GL, RF, and BF)
18	MAG (pelvis, thighs, shanks, and feet)		37	EMG (RF, and BF)
19	MAG (pelvis, thighs, and shanks)		38	EMG (TA, and GL)

*JAD means Joint Angles and Derivatives (angular velocity and acceleration).

**MAG means magnitude of 3D raw accelerometer and gyroscope.

***SAD means Segment Angles and Derivatives (angular velocity and acceleration).

5.3.3 CLASSIFICATION MODELS

In the scope of this thesis, **Long Short-Term Memory** (LSTM), **CNN**, and **Transformers** were explored since these models revealed high generalization ability and high performances in previous studies and are adequate for time series [123]–[125]. All models were implemented and evaluated in Matlab® (2023b, The Mathworks, MA, USA), running in a Hewlett-Packard computer (Intel® Core™ i7-4710MQ CPU @ 2.50 GHz processor and 16.0 GB random access memory).

Several empirical analyses were conducted to find the best LM decoding tool. Regarding LSTM, it was studied (i) the number of neurons (5, 10, 15, 20, 25, 30, 35, 40); and (ii) the number of *LSTM layers* (1, 2, 3). In the case of CNN, the hyperparameters studied were (i) the number of filters (8, 16, 32, 64, 128); (ii) the kernel size (10 to 100 with increments of 5); (iii) the number of convolutional layers (1, 2, 3); and (iv) the pooling layer (average and max pooling layer). The hyperparameters explored in the Transformer were (i) the number of encoder layers (1 and 2); (ii) the number of heads (2, 4, 8, 16, 32); and (iii) the embedding size (128, 256).

For three DL models, the following parameters were explored: (i) dropout rate (between 0% and 80% with increments of 10%); (ii) the batch size (8, 16, 32, 64, 128, and 254); (iii) the sequence length (80, 100, 120, 140, 160, 180, and 200); and (iv) the normalization method (robust, max-min, and z-

score). Furthermore, it was utilized (i) the adaptive moment estimation optimization algorithm to optimize the parameters of the neural networks, including weights and biases [126]; (ii) the focal cross-entropy loss to address potential class imbalance [127]; and (iii) various data augmentation techniques such as jittering, scaling, magnitude warping, and a combination of scaling and magnitude warping. These data augmentation techniques were employed to increase the diversity of the available data while preserving accurate labels [128], [129].

To determine the optimal hyperparameters and the best LM decoding tool, a leave-one-subject-out cross-validation (LOSOCV) was performed. Two participants, selected randomly from the fifteen participants in the study (a 25-year-old able-bodied female with a body mass of 68.3 kg and a height of 1.65 m, and a 27-year-old able-bodied male with a body mass of 83.0 kg and a height of 1.70 m), were chosen to validate and test the model, offline, respectively. Subsequently, the model was trained using data from the remaining thirteen participants.

5.3.4 EVALUATION METRICS

Six evaluation metrics were computed to assess the performance of the LM decoding tool, namely, the **ACC**, **Matthew's Correlation Coefficient** (MCC), **F1-score**, **success rate per class**, **computational load**, and **prediction time**.

The *computational load* (in ms) denotes the time necessary for the LM decoding tool to classify the LM upon receiving new data. The *prediction time* (in ms and as a percentage of the gait cycle) is determined by Equation 5.2, in which (i) $T_{critical}$ represents the critical instant; and (ii) $T_{prediction}$ is instant in which the LM decoding tool performs a classification. Thus, *prediction time* was computed and averaged for six transitions: St-LGW, LGW-St, LGW-SD, SD-LGW, LGW-SA, and SA-LGW. The *prediction time* was also assessed as a percentage of the gait cycle to understand at what phase of the gait cycle the new LM is decoded.

$$Prediction\ time = T_{critical} - T_{prediction} \quad (5.2)$$

5.3.5 EXPERIMENTAL VALIDATION

Once trained, the model was converted to the ONNX format, in order to be integrated into the high-level of the SmartOs system. This model conversion was done since the ONNX platform increases the

portability and interoperability of AI models [130]. After integrating the trained model into the SmartOs system, the LM decoding tool was evaluated under real-time procedures, as follows.

A. Participants

To validate the LM decoding tool in real-time, three participants were included: two able-bodied participants (one male and one female with an average age, body mass, and body height of 26.0 ± 1.00 years old, 76.5 ± 6.5 kg, and 167.5 ± 2.5 cm) and one female participant that suffered a stroke (age: 22 years old; body mass: 51.0 kg; body height: 160.0 cm; paretic side: right; stroke type: ischemic; stroke time: 9 months; FMA-LE: 26). It is noteworthy that the model training process did not involve these participants. The proposed control strategy was validated with the two able-bodied participants. All participants provided written and informed consent, considering the University of Minho Ethics Committee (CEICVS 006/2020).

B. Experimental Protocol

In the beginning, participants were instrumented with the sensor configuration that provided the best classification performance, along with the ankle orthosis. To ensure familiarity with the device, a 10-minute walking trial was performed wearing the SmartOs system operating under zero-torque control.

Once familiarized with the device, experiments were conducted with the SmartOs system operating under zero-torque control. In these experiments, able-bodied participants were asked to walk at different gait speeds, while the post-stroke patient was asked to walk at a self-selected speed, as summarized in Table 5.2. Firstly, participants walked at self-selected speeds. Then, participants were asked to walk at four different cadences, starting with 35 beats/minute until 50 beats/minute, with increments of 5 beats/minute. The values of the chosen cadences were higher and lower than the values chosen during the data collection performed to train the DL models. This was done to study how the LM decoding tool performs in speed conditions different from those the tool was trained.

During these experiments, the able-bodied participants walked in three different scenarios and, for each scenario, walked at different gait speeds. This validation aims to explore the robustness of the developed LM decoding tool in different environments. The first scenario (Figure 5.2) consists of the same environment where data were collected to train the DL model. It consists of an indoor scenario composed of 13 steps with dimensions of 18.0 cm (height), 110 cm (width), and 31.0 cm (depth). The second scenario (Figure 5.3 – left view) represents another indoor scenario composed of

8 steps with the same dimensions as scenario 1. The third scenario (Figure 5.3 – right view) is an outdoor scenario consisting of 13 steps with dimensions of 16.0 cm (height), 500 cm (width), and 30.0 cm (depth).

The protocol adopted for real-time experiments in the first scenario was the same performed during the data collection for training the DL models. For the second and third scenarios, participants completed a continuous circuit of nine task sequences, as depicted in Figure 5.3, namely: 1. standing for 10 seconds (St); 2. walking in a straight line for 3.5 meters (LGW); 3. ascending stairs (SA); 4. walking again in a straight line for 2.5 meters (LGW); 5. stopping in the standing position for 5 seconds (St), turning 180°, and stopping again in the standing position for more 5 seconds (St); 6. walking in a straight line for 2.5 meters (LGW); 7. descending stairs (SD); 8. walking in a straight line for an additional 3.5 meters (LGW); and 9. stopping in the standing position for 5 seconds (St). At task sequence number 5, the data corresponding to the turning task were posteriorly deleted, since the LM decoding was not trained under turning tasks. During this protocol, a researcher annotated the instant of transitioning between two consecutive LMs using the SmartOs' mobile graphical application (Figure 5.1). These events were then inspected by two additional researchers to ensure accuracy in labeling the transition instants.

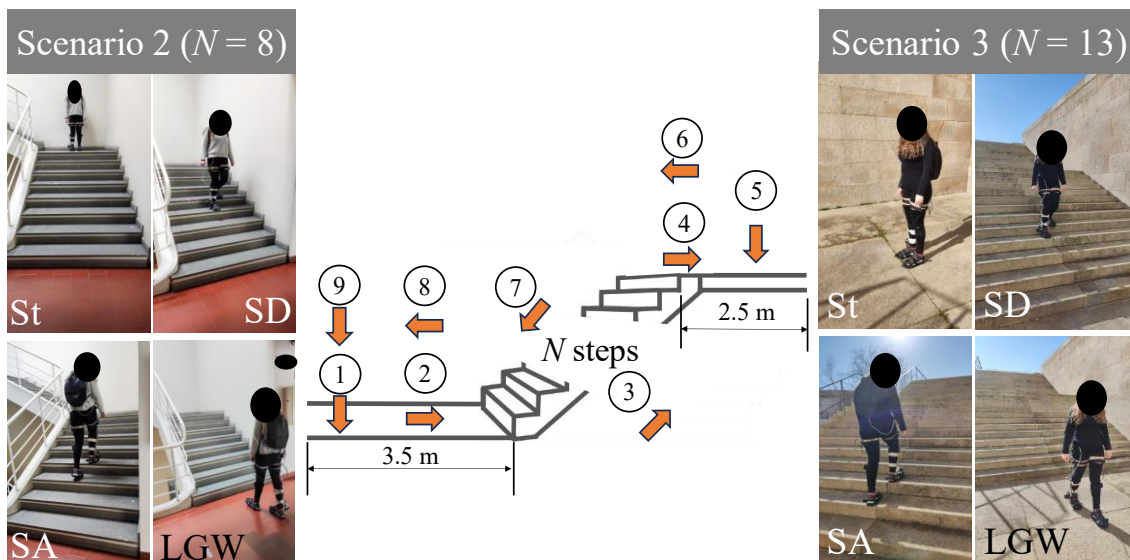


Figure 5.3 – A healthy test participant performing the four LMs (St, LGW, SD, SA) in the second scenario (left view) and the third scenario (right view). Positions (1) and (9) denote the starting and ending positions, respectively.

Table 5.2 – Identification of the conditions for real-time tests performed by the able-bodied participants and a post-stroke patient

Participant	Control Mode	Scenario	Cadence
Able-bodied	Zero-torque mode	1	Self-selected
			35 beats/minute
		2	40 beats/minute
			45 beats/minute
Post-stroke	Zero-torque mode	3	50 beats/minute
		2	Self-selected

5.4 RESULTS

5.4.1 DATA BALANCING

A total of 954,298 samples were collected to train the DL models, distributed as follows: 211,381 for the St task, 290,710 for the LGW, 221,928 for the SD, and 230,279 for the SA. This analysis is complemented by Figure 5.4, which shows the mean and standard deviation for each class, considering the number of participants. Figure 5.4 shows that the St and SD tasks represent the minority classes, while the LGW is the majority class. Nevertheless, it was observed that the mean number of samples per class is relatively consistent, ranging from 22% to 30%. Furthermore, the amount of each class per participant shows minimal variability, as indicated by low standard deviation values ranging from 1.4% to 2.3%. Based on these findings, the dataset is considered to be balanced.

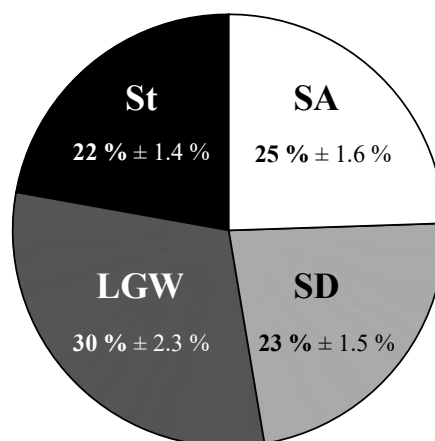


Figure 5.4 – Mean and standard deviation values of the sample distribution per class across subjects. St, LGW, SD, and SA mean Standing, Level-Ground Walking, Stair Descent, and Stair Ascent, respectively.

5.4.2 INPUT DATA ANALYSIS

Table 5.3 shows the results obtained by the LOSOCV method for each DL model and for each set of inputs. The achieved results indicated that the lower performances for all DL models (LSTM, CNN, and Transformers) were verified when using the RMS EMG as input (ACC, MCC, and F1-score below 0.794 ± 0.078 , 0.561 ± 0.131 , and 0.664 ± 0.098 , respectively). Among these data, it was also observed that using RMS EMG signals from the *tibialis anterior* and *gastrocnemius lateralis* muscles provided similar performances to the ones achieved when combining these muscles with *rectus*, and *biceps femoris* muscles.

Within the joint angle data type, all DL models showed their weakest performance (average ACC, MCC, and F1-score between 0.915 and 0.954, 0.796 and 0.883, and 0.846 and 0.912, respectively) when using the angles of both ankles together with their derivatives (angular velocities and accelerations) as input. Conversely, the models performed best when the angles, angular velocities, and angular accelerations of the knees and hips were used as input (average ACC, MCC, and F1-score between 0.976 and 0.980, 0.937 and 0.950, and 0.953 and 0.962, respectively).

Concerning the dataset composed of the magnitude of 3D data derived from accelerometers and gyroscopes, the three DL models showed their worst performance when using these input data from pelvic IMU only (average ACC, MCC, and F1-score between 0.482 and 0.900, 0.306 and 0.765, and 0.318 and 0.820, respectively). Conversely, the best performance was observed with the magnitude of 3D acceleration and angular velocity from the pelvic, thigh and shank IMUs for the LSTM and Transformer models (average ACC, MCC, and F1-score between 0.968 and 0.979, 0.917 and 0.947, and 0.938 and 0.960, respectively), and from the thigh and shank IMUs specifically for the CNN (average ACC, MCC, and F1-score of 0.975 ± 0.007 , 0.935 ± 0.019 , and 0.952 ± 0.014 , respectively).

Finally, when considering the data type combining the segment angles along with their derivatives, for all DL models, it was verified that using (i) the pelvic segment angles and their derivatives reduced the models' performance (average ACC, MCC, and F1-score between 0.732 and 0.794, 0.471 and 0.571, and 0.581 and 0.662, respectively); and (ii) the thigh and shank segment angles and their derivatives improved the model performance (average ACC, MCC, and F1-score between 0.979 and 0.982, 0.946 and 0.953, and 0.960 and 0.965, respectively).

Overall, the type of data that provided the best performance across all DL models was achieved using the thigh and shank segment angles along with their derivatives as input data.

Table 5.3 – LOSOCV metrics for all input combinations and DL models. The best and the worst results are colored in blue and red, respectively. The highest performance achieved is shaded in green color

Input ID	LSTM			CNN			Transformer		
	ACC*	MCC*	F1-score*	ACC*	MCC*	F1-score*	ACC*	MCC*	F1-score*
1	0.954 (0.023)	0.883 (0.051)	0.912 (0.040)	0.940 (0.023)	0.853 (0.051)	0.889 (0.040)	0.915 (0.030)	0.796 (0.064)	0.846 (0.051)
2	0.967 (0.023)	0.917 (0.054)	0.937 (0.042)	0.967 (0.019)	0.915 (0.046)	0.936 (0.035)	0.931 (0.039)	0.837 (0.079)	0.874 (0.066)
3	0.978 (0.013)	0.945 (0.032)	0.958 (0.025)	0.971 (0.024)	0.928 (0.055)	0.946 (0.043)	0.969 (0.019)	0.921 (0.046)	0.941 (0.036)
4	0.973 (0.010)	0.931 (0.026)	0.949 (0.019)	0.966 (0.014)	0.913 (0.034)	0.935 (0.026)	0.950 (0.024)	0.877 (0.052)	0.907 (0.042)
5	0.974 (0.016)	0.934 (0.039)	0.950 (0.030)	0.968 (0.024)	0.920 (0.055)	0.940 (0.043)	0.965 (0.001)	0.913 (0.059)	0.934 (0.046)
6	0.980 (0.010)	0.950 (0.024)	0.962 (0.019)	0.979 (0.013)	0.945 (0.031)	0.959 (0.024)	0.976 (0.010)	0.937 (0.027)	0.953 (0.020)
7	0.978 (0.011)	0.944 (0.028)	0.958 (0.022)	0.975 (0.015)	0.935 (0.036)	0.951 (0.028)	0.974 (0.012)	0.933 (0.031)	0.950 (0.024)
8	0.959 (0.011)	0.895 (0.028)	0.921 (0.021)	0.951 (0.017)	0.875 (0.039)	0.907 (0.030)	0.898 (0.025)	0.757 (0.052)	0.816 (0.041)
9	0.975 (0.011)	0.936 (0.029)	0.952 (0.022)	0.973 (0.010)	0.930 (0.026)	0.948 (0.019)	0.954 (0.011)	0.883 (0.026)	0.909 (0.020)
10	0.974 (0.011)	0.933 (0.028)	0.950 (0.021)	0.969 (0.011)	0.922 (0.027)	0.941 (0.021)	0.917 (0.021)	0.799 (0.045)	0.849 (0.036)
11	0.971 (0.009)	0.926 (0.024)	0.945 (0.018)	0.971 (0.009)	0.926 (0.023)	0.944 (0.018)	0.965 (0.009)	0.910 (0.023)	0.932 (0.017)
12	0.978 (0.007)	0.944 (0.019)	0.958 (0.015)	0.975 (0.007)	0.935 (0.019)	0.952 (0.014)	0.964 (0.013)	0.910 (0.032)	0.932 (0.025)
13	0.970 (0.007)	0.924 (0.019)	0.943 (0.014)	0.962 (0.010)	0.904 (0.025)	0.928 (0.019)	0.951 (0.018)	0.878 (0.042)	0.908 (0.032)
14	0.961 (0.014)	0.901 (0.035)	0.926 (0.027)	0.954 (0.022)	0.884 (0.053)	0.913 (0.040)	0.930 (0.021)	0.827 (0.047)	0.869 (0.037)
15	0.974 (0.014)	0.933 (0.034)	0.950 (0.026)	0.970 (0.013)	0.924 (0.032)	0.943 (0.025)	0.921 (0.032)	0.810 (0.065)	0.855 (0.054)
16	0.970 (0.015)	0.923 (0.037)	0.942 (0.029)	0.974 (0.007)	0.933 (0.018)	0.950 (0.014)	0.939 (0.016)	0.848 (0.037)	0.885 (0.029)
17	0.971 (0.012)	0.925 (0.031)	0.944 (0.023)	0.967 (0.016)	0.916 (0.038)	0.937 (0.030)	0.963 (0.014)	0.906 (0.034)	0.929 (0.026)
18	0.973 (0.014)	0.931 (0.033)	0.948 (0.027)	0.971 (0.011)	0.924 (0.027)	0.944 (0.020)	0.966 (0.016)	0.915 (0.038)	0.936 (0.029)
19	0.979 (0.008)	0.947 (0.020)	0.960 (0.015)	0.970 (0.014)	0.924 (0.035)	0.943 (0.027)	0.968 (0.013)	0.917 (0.031)	0.938 (0.024)

Input ID	LSTM			CNN			Transformer		
	ACC*	MCC*	F1-score*	ACC*	MCC*	F1-score*	ACC*	MCC*	F1-score*
20	0.965 (0.012)	0.911 (0.029)	0.933 (0.023)	0.960 (0.014)	0.898 (0.036)	0.923 (0.027)	0.930 (0.023)	0.8295 (0.05)	0.870 (0.041)
21	0.900 (0.033)	0.765 (0.068)	0.820 (0.055)	0.892 (0.034)	0.747 (0.068)	0.807 (0.055)	0.482 (0.039)	0.306 (0.035)	0.318 (0.034)
22	0.949 (0.021)	0.872 (0.048)	0.903 (0.038)	0.944 (0.020)	0.861 (0.043)	0.894 (0.036)	0.920 (0.026)	0.807 (0.056)	0.854 (0.044)
23	0.978 (0.007)	0.942 (0.018)	0.957 (0.014)	0.969 (0.013)	0.920 (0.031)	0.940 (0.024)	0.971 (0.005)	0.926 (0.012)	0.945 (0.010)
24	0.944 (0.111)	0.883 (0.183)	0.909 (0.151)	0.945 (0.083)	0.879 (0.140)	0.905 (0.120)	0.927 (0.118)	0.848 (0.179)	0.881 (0.153)
25	0.980 (0.009)	0.948 (0.023)	0.961 (0.018)	0.978 (0.010)	0.944 (0.027)	0.958 (0.020)	0.975 (0.009)	0.937 (0.022)	0.953 (0.017)
26	0.982 (0.009)	0.953 (0.022)	0.965 (0.017)	0.979 (0.008)	0.946 (0.021)	0.960 (0.016)	0.980 (0.006)	0.948 (0.015)	0.961 (0.011)
27	0.976 (0.012)	0.939 (0.031)	0.954 (0.023)	0.970 (0.023)	0.925 (0.053)	0.944 (0.041)	0.968 (0.023)	0.921 (0.054)	0.940 (0.042)
28	0.947 (0.020)	0.869 (0.045)	0.933 (0.036)	0.937 (0.029)	0.846 (0.065)	0.883 (0.051)	0.929 (0.022)	0.826 (0.049)	0.868 (0.038)
29	0.967 (0.013)	0.915 (0.032)	0.936 (0.024)	0.964 (0.023)	0.910 (0.052)	0.932 (0.041)	0.969 (0.007)	0.920 (0.017)	0.940 (0.013)
30	0.972 (0.012)	0.929 (0.028)	0.946 (0.022)	0.966 (0.009)	0.913 (0.021)	0.934 (0.016)	0.958 (0.016)	0.894 (0.038)	0.920 (0.029)
31	0.975 (0.015)	0.936 (0.037)	0.95 (0.0297)	0.975 (0.013)	0.935 (0.033)	0.951 (0.025)	0.975 (0.009)	0.937 (0.023)	0.953 (0.017)
32	0.977 (0.013)	0.941 (0.033)	0.956 (0.025)	0.978 (0.008)	0.942 (0.022)	0.957 (0.017)	0.977 (0.012)	0.940 (0.030)	0.955 (0.022)
33	0.980 (0.009)	0.948 (0.023)	0.961 (0.017)	0.976 (0.016)	0.939 (0.037)	0.954 (0.030)	0.978 (0.010)	0.943 (0.026)	0.958 (0.020)
34	0.977 (0.010)	0.942 (0.025)	0.956 (0.019)	0.970 (0.015)	0.923 (0.037)	0.942 (0.029)	0.971 (0.016)	0.926 (0.039)	0.944 (0.030)
35	0.788 (0.053)	0.557 (0.086)	0.650 (0.074)	0.794 (0.062)	0.571 (0.089)	0.662 (0.082)	0.732 (0.061)	0.471 (0.099)	0.581 (0.076)
36	0.794 (0.078)	0.561 (0.131)	0.664 (0.098)	0.788 (0.085)	0.555 (0.148)	0.658 (0.114)	0.760 (0.062)	0.510 (0.105)	0.635 (0.096)
37	0.608 (0.122)	0.265 (0.184)	0.448 (0.133)	0.656 (0.122)	0.333 (0.181)	0.499 (0.134)	0.599 (0.119)	0.262 (0.171)	0.437 (0.127)
38	0.793 (0.095)	0.568 (0.154)	0.667 (0.121)	0.779 (0.096)	0.542 (0.158)	0.647 (0.124)	0.737 (0.066)	0.467 (0.105)	0.587 (0.082)

*The values inside curved brackets represent the standard deviation.

5.4.3 OFFLINE DL MODEL ANALYSIS

Overall, the results in Table 5.3 indicate that the LM decoding tool that provided the highest performance, for all metrics, was the LSTM model fed by segment angles, angular velocities, and angular accelerations of both thighs and shanks (average ACC, MCC, and F1-score of 0.982 ± 0.009 , 0.953 ± 0.022 , and 0.965 ± 0.017 , respectively). This model consisted of two *LSTM layers*, each comprising 20 neurons and separated by a *dropout layer* with a dropout rate of 20%. Following the second *LSTM layer*, the model included a *Fully Connected layer* with 10 neurons and a *Softmax layer*. Moreover, it was found a batch size of 64, a sequence length of 140, and the z-score method for normalization. Figure 5.5 depicts the best model architecture found.

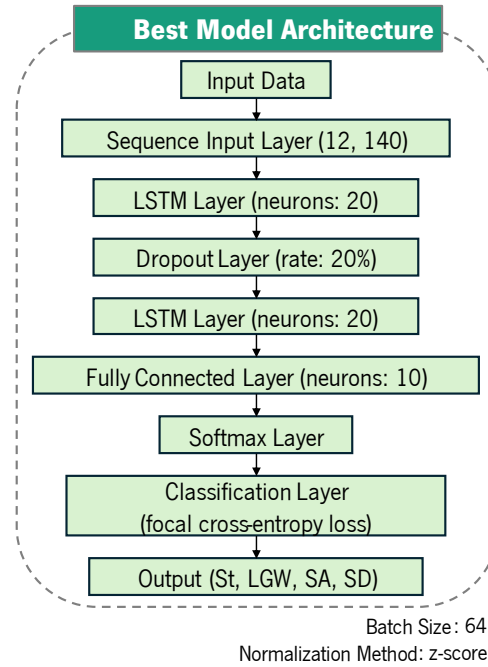


Figure 5.5 – Architecture of the best model found during the LOSOCV.

Figure 5.6 – left view presents the training and validation loss obtained during the training of the LSTM model. From Figure 5.6 – left view, it is verified that the validation loss followed the training loss, stabilizing around epoch number 60 (both training and validation losses are close and do not seem to decrease).

Table 5.4 presents the offline performances of the LSTM model fed by the segment angles, angular velocities, and angular accelerations of both thighs and shanks achieved during the model test procedure (ACC, MCC, and F1-score of 0.982, 0.952, and 0.964, respectively). The results presented in Table 5.4 are in accordance with the LOSOCV results across the three metrics, reaching values higher than 0.952. These results are confirmed by Figure 5.6 – right view that depicts the offline predictions made by the

proposed LM decoding tool in the test participant. From Figure 5.6 – right view, it is verified that the predicted labels followed the ground truth labels.

Overall, the LOSOCV and the offline test performances reveal the robustness and generalization ability of the developed LSTM model across diverse participants.

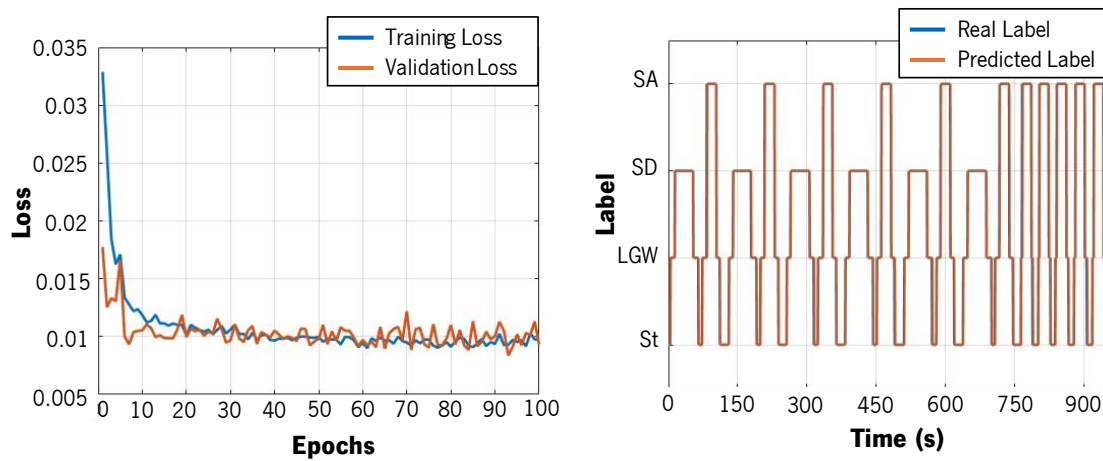


Figure 5.6 – Training and validation loss obtained during the model training procedure (left view) and offline classification of the LSTM model in the test participant (right view).

Table 5.4 – Offline test metrics

Input ID	NN*	ACC	MCC	F1-score
26	LSTM	0.982	0.953	0.965

*NN means Neural Network

5.4.4 ONLINE DL MODEL ANALYSIS

The best model found was tested under real-time conditions. A total of 550,308 predictions were made during real-time experiments with able-bodied participants. Table 5.5 shows the average and standard deviation of the computed metrics (ACC, MCC, and F1-score) across gait speeds, scenarios, and control modes. In general, the results presented in Table 5.5 show a high average (above 0.964) and low standard deviation (around 0.010) values for the three metrics, achieving an average ACC, MCC, and F1-score of 0.986 ± 0.004 , 0.964 ± 0.010 , and 0.973 ± 0.007 , respectively. In addition, these results indicate that the proposed LM decoding tool is robust to different speeds (controlled and self-selected speeds) and scenarios (indoor and outdoor, variable stair dimensions) since the achieved metrics for each speed and scenario are quite close.

Table 5.5 – Online test metrics for able-bodied participants

Scenario	Cadence	ACC	MCC	F1-score
1	Self-selected	0.990	0.973	0.980
	35 beats/min	0.989	0.969	0.978
	40 beats/min	0.989	0.970	0.979
	45 beats/min	0.991	0.976	0.982
	50 beats/min	0.989	0.972	0.979
2	Self-selected	0.979	0.944	0.959
	35 beats/min	0.980	0.948	0.964
	40 beats/min	0.981	0.950	0.963
	45 beats/min	0.982	0.952	0.965
	50 beats/min	0.978	0.941	0.956
3	Self-selected	0.987	0.966	0.974
	35 beats/min	0.988	0.966	0.975
	40 beats/min	0.984	0.958	0.969
	45 beats/min	0.983	0.953	0.966
	50 beats/min	0.984	0.958	0.969
Average $\pm$ STD		0.986 $\pm$ 0.004	0.964 $\pm$ 0.010	0.973 $\pm$ 0.005

Moreover, the LSTM model made 7,718 predictions in real-time with the post-stroke patient, since the experiment with this participant was performed at only one speed (self-selected), in a single scenario (scenario 2), and with the active orthosis operating under the zero-torque control. Table 5.6 shows that the LSTM model presents a high performance in the stroke participant, achieving an accuracy, MCC, and F1-score of 0.972, 0.927, and 0.946, respectively.

Table 5.6 – Online test metrics for the stroke patient

Scenario	Cadence	ACC	MCC	F1-score
2	Self-selected	0.972	0.927	0.946

Furthermore, Table 5.7 shows the success rate of the LM decoding tool for each LM. For both able-bodied and stroke subjects (i) the lowest value was registered for the St task (93.8 ± 2.17 % and 88.9%, respectively); and (ii) the highest success rate was verified during the SD task (99.1 ± 0.49 % and 99.5%, respectively), followed by the SA tasks (98.9 ± 0.94 and 95.7 %, respectively). The success rate for the

St, LGW, and SA tasks of the stroke patient was slightly lower than the one achieved by the able-bodied participants, as these were the tasks in which there were the most misclassifications (as verified in Figure 5.7).

Table 5.7 – Success rate (%) per LM

Participant	St	LGW	SD	SA
Able-bodied	93.8 ± 2.17	97.3 ± 1.05	99.1 ± 0.49	98.9 ± 0.94
Post-stroke	88.9	93.5	99.5	95.7

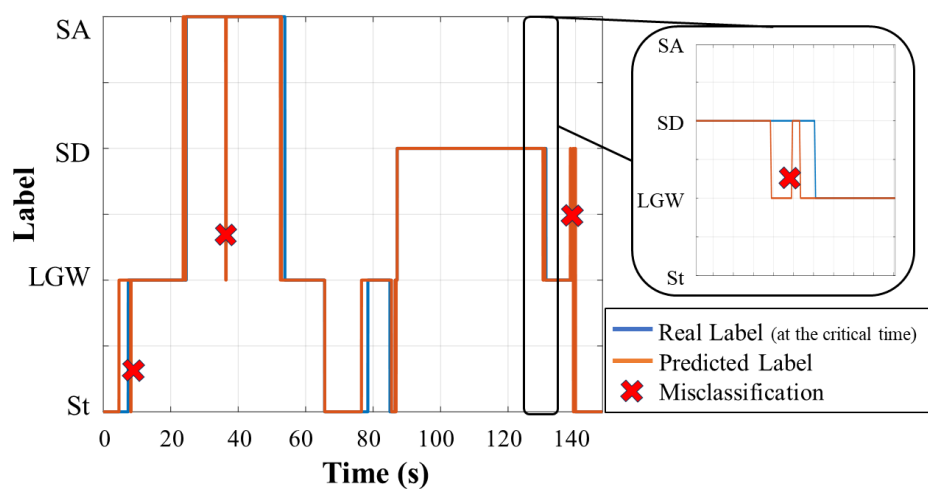


Figure 5.7 – Online classification of the LM decoding tool in the stroke patient.

Additionally, in terms of *computational load*, the average time per prediction was around 1.58 ± 0.42 ms. This indicates that from the moment the LM decoding tool receives the InertialLab data (consisting of right and left thigh and shank segment angles), calculates angular velocities and accelerations, and performs an LM classification, the proposed decoding tool typically takes about less than 2 ms.

Table 5.8 summarizes the *prediction time*, in milliseconds, and as a percentage of the gait cycle. From the results exhibited in Table 5.8, the St-LGW transition represents the transition that is detected earliest, i.e., with higher *prediction time* before reaching the upcoming LM, presenting averages of 860 ± 178 ms (72.3 ± 7.93 % of the previous gait cycle). On the other hand, the LGW-St corresponds to the transition detected with fewer *prediction times in advance* (241 ± 294 ms, corresponding to 93.1 ± 10.5 % of the previous gait cycle).

Overall, the results of Table 5.8 indicate that all LMs were decoded during the swing phase of the gait cycle that precedes the new LM, i.e., all LMs were predicted in advance.

Table 5.8 – Average *prediction time* in milliseconds (orange) and as a percentage of the gait cycle (blue)

St to LGW	LGW to SA	SA to LGW	LGW to SD	SD to LGW	LGW to St	Average $\pm$ STD
860 $\pm$ 178	507 $\pm$ 252	465 $\pm$ 243	532 $\pm$ 337	308 $\pm$ 227	241 $\pm$ 294	482 $\pm$ 227
72.3 $\pm$ 7.93	85.0 $\pm$ 7.38	84.9 $\pm$ 8.70	82.7 $\pm$ 11.5	90.3 $\pm$ 7.68	93.1 $\pm$ 10.5	84.7 $\pm$ 6.59

5.5 DISCUSSION

This research was carried out in the field of robotic gait assistance and rehabilitation with the ultimate goal of assisting impaired subjects in everyday locomotion tasks. This work advances the current state-of-the-art, by exploring the best sensor data and classification algorithms to build a DL decoding tool able to predict four LMs (St, LGW, SD, and SA) and transitions among them while considering the preferred gait speeds of stroke patients (below 2.7 km/h). The applicability of the LM decoding tool was tested under real-time conditions with two able-bodied participants and one post-stroke patient, across different speeds (self-selected and controlled) and scenarios (indoor and outdoor with stairs and flat floors with different dimensions).

5.5.1 INPUT DATA ANALYSIS

Thirty-eight input combinations were deeply explored to build a generalized LM decoding tool. The results showed that the use of the **RMS EMG data offered the lowest performances** (ACC ranging from 0.599 to 0.794), **regardless of the DL algorithm**. The achieved performances were lower than the ones presented in previous studies [62], [114], [115] ($0.949 < \text{ACC} < 0.997$). This lower performance may be explained by the single use of one time-domain feature (the RMS EMG) whereas previous studies [62], [114], [115] have combined this feature with other EMG features (mean absolute value, waveform length, slope sign changes, and zero-crossing). Moreover, it was verified that using RMS EMG from *tibialis anterior* and *gastrocnemius lateralis* revealed ACC values ($0.739 < \text{ACC} < 0.793$) closer to the ones obtained when using these two muscle types along with the *rectus* and *biceps femoris* ($0.760 < \text{ACC} < 0.794$). However, these results are not in line with literature evidence, since both *rectus* and *biceps femoris* provide a valuable contribution in terms of stability and propulsion during SA and SD tasks [131].

Regarding joint angle input type, the **combination of hip and knee joint angles and their derivatives as input yields the most accurate classifications** ($0.976 < \text{ACC} < 0.980$). These results slightly exceed the literature findings [117], where the use of hip and knee joint angles and their

derivatives for LM decoding revealed ACCs of 0.976. The use of **ankle angles and their derivatives provided the worst performances** ($0.915 < \text{ACC} < 0.954$). This result may be explained by the fact that the flexion/extension of the knee and hip, and consequently the range of motion of these joints, present a higher variation between the different LMs, whereas the angle of the ankle is more identical across LMs.

With respect to the dataset composed of the magnitude of **3D data derived from accelerometers and gyroscopes, the use of pelvic, thigh, and shank IMU sensors revealed the best results** ($0.970 < \text{ACC} < 0.979$). Despite this type of data being not used in the reviewed studies, the IMU combinations that provided the best results (ACC ranging from 0.932 to 0.984) were those positioned in the same segments (pelvis, thighs, and shanks) used in studies [41], [43]–[46], [116], [117]. Moreover, the results indicated the **worst LM decoding performance when using the magnitude of the 3D accelerometer and gyroscope data from the pelvic IMU only** ($0.482 < \text{ACC} < 0.900$). This can be explained by the fact that the pelvic segment is the most stable segment during locomotion. Thus, it may not present significant changes in such a way that it is easy to distinguish which LM the user is in.

Considering segment angle data type, **the use of pelvic segment angles and their derivatives as input showed the lowest performances** ($0.732 < \text{ACC} < 0.794$), as verified when using the magnitude of 3D accelerometer and gyroscope data. On the other hand, **the highest performance was verified when using the thigh and shank segment angles and their derivatives** as input ($0.979 < \text{ACC} < 0.982$). These results are aligned with those achieved in studies [43], [44], since the use of thigh and shank segment angles and derivatives revealed ACCs ranging from 0.930 and 0.983, respectively.

Overall, there seems to be a tendency to achieve high LM decoding performances when using kinematic information extracted from IMU sensors placed at the shank and thigh segments (i.e., hip and knee joint angles, thigh and shank segment angles, or magnitude of accelerometer and gyroscope data at these segments). This tendency could be attributed to the high variation in knee and hip flexion and extension, as well as the range of motion of these joints, across different LMs.

5.5.2 OFFLINE PERFORMANCE EVALUATION

From the benchmark analysis between types of data and DL algorithms, **the best LOSOCV results were achieved for an LSTM fed by thigh and shank segment angles and derivatives**

(average ACC of 0.982 ± 0.009). From the literature analysis, the LSTM model was not employed by studies [41], [43]–[46], [62], [114]–[117] in decoding LMs when using wearable assistive devices. A direct comparison cannot be made between the results of this study and the literature, as the protocols and the classified LMs differ among them. Nonetheless, the obtained performances are close to the ones obtained in the study [45] (ACC = 0.984). The study [45] used a Multilayer Feedforward Neural Network to decode ST, LGW, SA, SD, RA, and RD tasks. Despite decoding RA and RD tasks, the study [45] required a training step of 18 minutes for each user. On the other hand, the achieved average ACC was promising since it was closer to the highest ACC found in the literature (99.7%) [62].

In addition, both the LOSOCV and the model offline test performances indicate that the proposed LM decoding tool **demonstrates strong generalization capabilities across participants**.

5.5.3 ONLINE PERFORMANCE EVALUATION

Overall, the results obtained during **real-time test conditions for both health and stroke subjects are similar to the ones achieved during the LOSOCV and offline test procedures**. Despite being slightly inferior, the results obtained for the stroke patient (ACC = 0.972) are comparable to those achieved for the able-bodied participants (ACC = 0.986). This slight reduction in the evaluation metrics was also verified in the study [43] and it may be related to the asymmetrical and abnormal gait patterns typically performed by stroke patients [7]. The obtained model showed potential for decoding LMs with a stroke patient, although it was trained on data from able-bodied participants.

On the other hand, none of the existing tools [41], [43]–[46], [116], [117] evaluated the model performance at the preferred speeds of neurologically impaired users (below 2.7 km/h). At this level, **the proposed LM decoding tool was demonstrated to be robust to different cadences**, corresponding to gait speeds ranging from 1.0 to 1.6 km/h ($0.988 < \text{ACC} < 0.991$).

Additionally, in an attempt to advance studies [41], [43]–[46], [116], [117], the robustness of the model was analyzed in relation to different scenarios. The DL decoding tool was tested in different environments (indoor and outdoor), with a different number of steps (8 and 13), with different step dimensions (height: 16.0 - 18.0 cm; width: 110 – 500 cm; and depth: 30.0 - 31.0 cm), and with a different order of task execution. **The proposed LM decoding tool proved to perform consistently in scenarios other than those adopted during tool training**, revealing ACCs ranging from 0.978 to 0.991.

Furthermore, the **SD and SA tasks provided the highest success rate** for both able-bodied and stroke subjects, with values ranging from 95.7% to 99.1%. These results are in line with those pointed out by studies [44]–[46], [117]. The **St task presented the lowest success rate** (88.9% - 93.8%). This result may be explained by the fact that in the transition between St and LGW, a small intention to start walking (e.g., by bending the knee) is immediately detected by the LM decoding tool as the LGW task, although the user still has both feet on the ground (the ground truth is still St task). This phenomenon may reduce the success rate in the St task.

The proposed LM decoding tool presented a **low computational load** (1.58 ± 0.42 ms) to perform classification upon receiving new sensor data. This computational load is within the timing requirements of the high-level of the SmartOs system (10 ms, operating at 100 Hz). Considering that the natural frequency of human motion during walking tasks is less than 2 Hz (i.e., 500 ms), the proposed LM decoding tool works fast enough to decode human LMs [132].

It is noteworthy that the assertiveness of LM decoding tools is critical since misclassifications can cause the wearable assistive device to adopt inappropriate gait patterns, potentially causing discomfort to the users [14]. However, the adoption of inappropriate gait patterns can result not only from misclassifications but also from delays in decoding the new LMs [119]. Despite the high accuracies reported, most of the reviewed studies recognize the new LM after the user has already entered on it [41], [45], [46], [62], [114]–[117]. The decoding delays typically range from 50.0 to 1897.9 ms.

Only two studies ([43], [44]) demonstrated the ability to predict specific LMs. The study [44] successfully predicted the transition from (i) SA to LGW in 10.7 ± 9.88 ms; (ii) SD to LGW in 78.7 ± 130.0 ms; and (iii) LGW to SA in 185.3 ± 56.9 ms. However, the detection of the LGW-SD transition occurred 40.0 ± 107.5 ms after the critical instant. In the study [43], the following transitions were predicted in advance: (i) SD-LGW at 0.70 ± 58.7 ms, (ii) LGW-SA at 5.40 ± 74.6 ms, (iii) SA-LGW at 46.7 ± 46.6 ms, and (iv) LGW-SD at 78.5 ± 25.0 ms. Nevertheless, the study [43] required offline training to create a user-specific decoding model for each participant prior to real-time experiments. In light of these findings, **the proposed LM decoding tool outperforms the aforementioned studies** ([41], [43]–[46], [62], [114]–[117]) **by predicting upcoming LMs with an average prediction time of 482 ± 227 ms**. Further, the average *prediction time* per transition was always positive (ranging from 241 to 860 ms), which means that, **across the six possible transitions** (St-LGW, LGW-SA, SA-LGW, LGW-SD, SD-LGW, and LGW-St), **the upcoming LM was decoded in advance, on average**. Translating these results as a percentage of the gait cycle (from 72.3% to 93.1%), it can be assumed that the next LM was decoded, on average, between the mid- and terminal swing of the gait cycle preceding the upcoming LM [133].

In addition, the St-LGW transition was decoded with a higher *prediction time* (860 ± 178 ms). This result could be explained by the possibility that during the St task, subtle movements could indicate the imminent onset of the LGW task. Conversely, the LGW-St transition presented the lowest *prediction time* (241 ± 294 ms). The high standard deviation value suggests that, at this transition, the participants may be not timely assisted by the SmartOs system in some cases, i.e., the assistance could change after the critical instant. This can be related to the fact that the LGW-St transition may involve a more abrupt shift by the user, making it difficult to predict the St task.

5.6 CONCLUSIONS

This work offers two contributions to the state of the art: (i) to **investigate the best fusion of sensor data and classification algorithms** to build a DL decoding tool capable of predicting in advance four LMs (St, LGW, SD, and SA) and transitions between them; and (ii) to develop an **LM decoding tool the timely decode four LMs in advance**.

This research concludes that, for decoding LMs, the use of (i) **RMS EMG features is not sufficient**; (ii) **thigh and shank segment angles as input to an LSTM provide the best performances**. Furthermore, the proposed tool was found to be accurate in both offline and online testing with healthy and stroke participants, presenting a **low computational load**. In addition, the tool proved to be **robust to different walking cadences and different scenarios**.

These conclusions highlight the suitability of the developed LM decoding tool to foster the development of LM-driven trajectory control strategies (detailed in Chapter 6) that timely adapt the assistance of wearable assistive devices according to the LM decoded.

Although the proposed LM decoding tool showed promising results, there are still opportunities for improvement. Specifically, there is a need to (i) conduct additional real-time validation procedures with more participants, including both able-bodied individuals and those with varying degrees of neurological impairments; (ii) extend the decoding capabilities to other LMs, particularly RA and RD, and transitions; and, (iii) improve the prediction performance for LGW-St transitions to increase the *prediction time*.

6. ASSIST-AS-NEEDED CONTROL STRATEGIES

This chapter begins with an introduction regarding the trends of assistive control strategies applied for robot-based gait training. It then describes the implemented hierarchical control architecture, focusing on the development and validation of the assistive control strategies investigated in this thesis: **AAN LM-driven trajectory control**, **AAN EMG-based control**, and **AAN HITL control**. These strategies were designed, implemented, and validated with healthy participants using the SmartOs system. The potential rehabilitation benefits of each assistance strategy are reviewed and discussed. The chapter concludes with a comprehensive overview of the proposed assistive control strategies.

6.1 INTRODUCTORY INSIGHT

Bio-inspired control architectures have begun to emerge, inspired by the principles and organization of the human motion control system [9]. These architectures aim to efficiently implement user-oriented control strategies and facilitate synergistic and continuous interaction between the user and the wearable assistive device, thereby enhancing brain plasticity [134]. For that, these architectures may include low-, mid-, and high-level controls that are hierarchically organized to address the physical interactions between the user, the environment, and the device. The design and development of the hierarchical control architecture of the SmartOs system followed these research directions and exploited the potential of different assistive control strategies, as described in this chapter.

According to studies [37], [134], advanced technology should be used rationally. It seems that **post-stroke patients may benefit more from training with wearable assistive devices when the active participation of the patient is invoked**. These results may be due to the fact that spontaneous neuroplasticity phenomena occur with greater intensity in the initial acute and sub-acute phases of rehabilitation after stroke. In this sense, **patients' active participation should be encouraged** to achieve rapid neuromuscular recovery during rehabilitation training.

Recent trends suggest that user-oriented assistance that encourages user participation may be achieved through the use of **AAN control strategies integrated into wearable assistive devices** [29]–[31], [33], [37]. AAN control strategies are focused on dynamically adjusting the level of assistance based on the user's real-time performance and locomotion needs, ensuring that the wearable assistive device assists movement only when and as much as required. **The goal is to encourage the user's active participation and muscle engagement while correcting the joint pattern during the execution of the walking motion** [29]–[31], [33], [37].

This Ph.D. thesis progresses the current literature by proposing the development of three AAN control strategies, as detailed below:

1. **Locomotion Mode-driven Trajectory Control:** a control responsible for mapping the user's locomotion intention and generating reference trajectories according to the desired/intended LM;
2. **Assist-As-Needed Electromyography-based Control:** a control combining position and torque controllers to adjust the orthosis assistance according to the user's muscular needs and joint pattern;
3. **Human-in-the-Loop Control:** a control designed to optimize the user metabolic cost by modifying control variables, namely, torque peak magnitudes.

6.2 LOCOMOTION MODE-DRIVEN TRAJECTORY CONTROL

6.2.1 CRITICAL ANALYSIS OF RELATED WORK

Often, wearable assistive devices have been equipped with non-intrusive sensor configurations and sophisticated algorithms to decode LMs, with the aim of tailoring the robot's assistance to help users perform their daily mobility tasks.

From the literature, only five studies have adapted the assistance of the wearable assistive device attending to the user's decoded LM [40], [42], [43], [116], [117]. In the studies [40], [42], a two-level hierarchical control design was followed. In the study [40], a constant torque of 10 N.m was provided by an ankle orthosis (low-level) when the SD task was recognized (high-level). For that, FSR sensors embedded in the orthosis foot were used to detect the gait cycle phase. Then, the LM was decoded, and the constant torque was provided. The torque was delivered during (i) the first 50% of the gait cycle to support the ankle joint motion when the leg without assistance was in the swing phase; (ii) the last 20% of the gait cycle to guarantee that the foot was performing plantar flexion before touching the next stair step. In the study [42], a two-level hierarchical control was designed to provide a phase-locked assistive torque (low-level) when an LM (among the Sit, St, LGW, SA, and SD tasks and transitions between them) was recognized (high-level). After recognizing the LW, SA, and SD tasks, a gait phase estimation algorithm was employed such that the most suitable phase-locked assistive torque was provided. The provided torque was adopted from public databases with joint trajectories recorded during locomotion-related activities [133], [135]–[137]. During the Sit and St tasks, no torque was provided. Nonetheless, torque

patterns modeled according to the body mass of each participant were delivered during Sit-St or St-Sit transitions. These transitions were detected based on the hip joint angles, using a threshold algorithm.

On the other hand, the studies [43], [116], [117] followed a three-level hierarchical control architecture. In the study [117], the high-level presented a gait phase estimation algorithm using IMU signals to segment the input data into strides. Based on these strides, the LM (LGW, SA, and SD) was decoded through a CNN. A Parameter Optimal Iterative Learning Control method was implemented in the mid-level. This method was designed for a soft lower limb exoskeleton to provide hip and knee assistance according to the tension of Bowden cables. The tension of these cables was modeled according to the hip and knee joint moments when performing the LW, SA, and SD tasks. The low-level was responsible for driving the exoskeleton according to the tension of the Bowden cables.

The high-level developed in the study [43] was different from the one developed in the study [117]. Firstly, the LM was distinguished between static and dynamic tasks at the high-level. Then, in the case of a dynamic task, the LM was classified (among LW, SA, and SD tasks), followed by a gait phase estimation algorithm to distinguish the stance from the swing phase. During the stance phase, three other subphases (heel-strike, heel-off, and toe-off) were identified at the high-level. In addition, the mid-level developed in the study [43] was hybrid. It used a zero-torque mode during the St task and the swing phase of LW, SA, and SD tasks in an attempt to reduce the constraints associated with the actuator's frictions. Moreover, during the first and second subphases (from the heel strike to heel-off events and from heel-off to toe-off events, respectively) of the SA task, the knee should perform the extension and flexion movements, respectively. Based on these assumptions, the knee exoskeleton provided a closed-loop torque control to extend and flex the knee joint, assisting the user during the first and the second subphases of the SA task. For the stance phase of the LW and SD tasks, the muscles around the knee joint provide negative torque to help the knee to move and avoid excessive knee flexion, supporting the human body. For this reason, an open-loop damping control was adopted to provide resistance at the knee joint to support the body and absorb the shock. The low-level was responsible for generating assistive commands as a response to the comparison between the desired torque (generated by the mid-level) and the measured torque (measured by an embedded load cell).

In the study [116], another three-level hierarchical control was adopted to assist the St, LGW, SA, and SD tasks, and transitions between them. The high-level was responsible for decoding LMs based on a threshold algorithm (to distinguish between static and dynamic tasks) and a Fuzzy-logic-based algorithm (to distinguish between LGW, SA, and SD tasks). The mid-level controller employs adaptive oscillators to

track the desired torque curve, while the low-level controller drives the motors to maintain the force feedback loop.

Additionally, **providing efficient assistance according to the decoded user's LM implies an accurate and timely identification of the user's intentions**. This is of utmost importance since the higher the anticipation time in identifying the LM, the more time remains to switch the control to assist the users according to their needs timely. This means that, ideally, the upcoming LM should be predicted before its occurrence, in order to adapt the assistance of the wearable assistive device according to the LM decoded. Considering the five studies that adapted the assistance according to the decoded LM, only the study [43] demonstrated the ability to predict and assist specific LMs. The study [43] successfully predicted the transition from (i) SD-LGW at 0.70 ± 58.7 ms, (ii) LGW-SA at 5.40 ± 74.6 ms, (iii) SA-LGW at 46.7 ± 46.6 ms, and (iv) LGW-SD at 78.5 ± 25.0 ms. Nevertheless, the study [43] required offline training to create a user-specific decoding model for each participant prior to real-time experiments, and the assistance was only provided during the stance phase.

Despite recent advances, **it is still unclear how to control the device to properly and timely assist users according to their locomotion intentions**. The available studies are limited by (i) only actively assisting during specific phases of the gait cycle (stance/swing or between gait cycle events) [40] [43] or LMs [42], [117]; (ii) the adaptation the control according to the decoded LM occurs after the critical instant (i.e., after the user enters on the new LM) [40], [42], [43], [116], [117]; (iii) testing the control performance in a single scenario, which is commonly used to train the LM decoding tool; and (iv) only address the walking speeds typically adopted by able-bodied users. This research advances the current state-of-the-art by proposing a **three-level assistive control strategy to timely adapt the assistance of the SmartOs system according to the decoded LM** (among St, LGW, SA, and SD), while actively assisting throughout the entire gait cycle. For that, the proposed control strategy integrates the DL tool developed in Chapter 5 into the high-level of the proposed control strategy. The robustness of the proposed LM-driven trajectory control was assessed (i) **in different scenarios** (indoor and outdoor); and (ii) **in a range of speeds**, all within the preferred values of stroke patients.

6.2.2 METHODOLOGY

A. Hierarchical Control Architecture

Once the optimal fusion between sensor data and DL algorithms has been found for decoding LMs (Chapter 5), a hierarchical three-level control strategy was developed to adapt the assistance of

the SmartOs system according to the output of the LM decoding tool (i.e., a classification between St, LGW, SA, or SD). The proposed control strategy is presented in Figure 6.1.

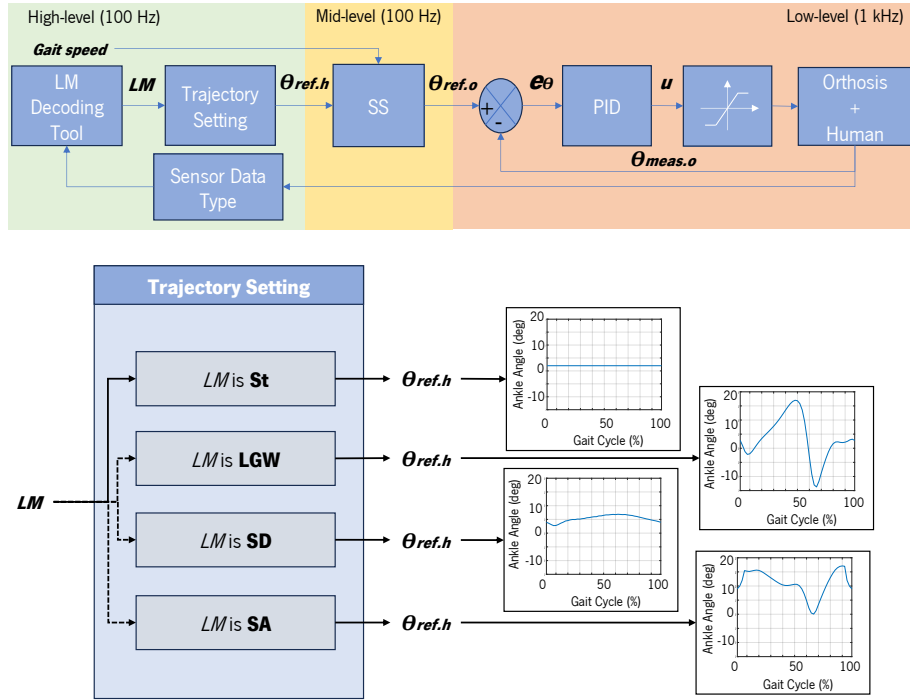


Figure 6.1 – Proposed hierarchical control architecture. LM is the predicted LM. $\theta_{ref,h}$ and $\theta_{ref,o}$ are the human and orthosis ankle joint reference angles, respectively. $e\theta$ is the orthosis position error. u is the Proportional-Integral-Derivative (PID) command. SS is a speed scaling block achieved by (2). PID stands for the PID controller.

The high-level runs the LM decoding tool. As depicted in Figure 6.1, new input data from the InertialLab system arrives at the LM decoding tool (*LM Decoding Tool* block) at 100 Hz. Therefore, the DL model provides a new classification every 10 ms. This classification is used to update a 3-sample buffer that contains the two previous classifications. The output of the 3-sample buffer was used together with the gait cycle phase to determine the human reference trajectory of the ankle joint angle ($\theta_{ref,h}$) through the *Trajectory Setting* block. This block is responsible for updating the $\theta_{ref,h}$ according to the decoded LM. The set $\theta_{ref,h}$ will assist the user in performing the decoded LM, i.e., a trajectory that supports the user during the St, LGW, SA, or SD tasks. The trajectories (depicted in Figure 6.1) were obtained from the dataset collected for developing the LM decoding tool (Chapter 5).

Next, the *Speed Scaling* block that operates at 100 Hz, receives the $\theta_{ref,h}$ generated by the *Trajectory Setting* block and the gait speed. This occurs at the mid-level of the architecture. The $\theta_{ref,h}$

is interpolated to the low-level control frequency (1 kHz), through Equation 2 found in the study [138], in which GS is the gait speed.

$$\text{Speed Scaling} = 107.32 - 34.62 \times GS \quad (6.1)$$

The low-level controller works at 1 kHz. It compares the $\theta_{ref.o}$ with the measured ankle angle ($\theta_{meas.o}$), calculating the orthosis position error ($e\theta$). The $e\theta$ is then fed into the Proportional-Integral-Derivative (PID) controller (PID block) that is configured with proportional, integral, and derivative gains set to 95.0, 1.5, and 1.5, respectively. The PID controller generates a PID command (u), which is constrained by a saturator to the maximum and minimum values of 2500 and -2500. This command is then interpreted by the ankle orthosis, resulting in the generation of the corresponding motor torque to follow the desired position according to the decoded LM.

B. Experimental Validation

To validate the proposed control strategy, two able-bodied participants (one male and one female) were involved, presenting an average age of 26.0 ± 1.00 years, an average body mass of 76.5 ± 6.5 kg, and an average body height of 167.5 ± 2.5 cm. Both participants provided written informed consent following the University of Minho Ethics Committee (CEICVS 006/2020).

In the beginning, participants' gender, age, body height, and body mass were recorded. They were then instrumented with the InertialLab system and ankle orthosis, as illustrated in Figure 6.2. To ensure familiarity with the device, a 10-minute walking trial was performed using the SmartOs system with zero-torque control.



Figure 6.2 – A male participant instrumented with the InertialLab and SmartOs systems.

After familiarization, participants performed several trials at different walking speeds and scenarios with the SmartOs system in active mode, i.e., LM-driven trajectory control. They walked through three different scenarios, namely scenario 1 (shown in Figure 5.2) and scenarios 2 and 3 (shown in Figure 5.3). Moreover, participants walked at four gait speeds imposed by the SmartOs system. The selected gait speeds cover those preferred by stroke patients, i.e., less than 2.7 km/h, ranging from 1.0 to 1.6 km/h.

The protocol adopted to evaluate the proposed control strategy was the same as that used to collect data to train and evaluate the LM decoding tool (see Chapter 5). This means that for the first scenario, participants were instructed to complete a continuous circuit of nine task sequences, namely, 1. standing for 10 seconds (St); 2. walking in a straight line for 2.5 meters (LGW); 3. descending stairs (SD); 4. walking again in a straight line for 3.5 meters (LGW); 5. stopping in the standing position for 5 seconds (St); 6. walking in a straight line for 3.5 meters (LGW); 7. ascending stairs (SA); 8. walking in a straight line for an additional 2.5 meters (LGW); and 9. stopping in the standing position for 5 seconds (St) (Figure 5.2). With respect to the second and third scenarios, the protocol adopted consisted of: 1. standing for 10 seconds (St); 2. walking in a straight line for 3.5 meters (LGW); 3. ascending stairs (SA); 4. walking again in a straight line for 2.5 meters (LGW); 5. stopping in the standing position for 5 seconds (St), turning 180°, and stopping again in the standing position for more 5 seconds (St); 6. walking in a straight line for 2.5 meters (LGW); 7. descending stairs (SD); 8. walking in a straight line for an additional 3.5 meters (LGW); and 9. stopping in the standing position for 5 seconds (St) (Figure 5.3). The data corresponding to the turning task at sequence number 5 were later deleted, as the LM decoding was not trained for turning tasks.

To evaluate the performance of the LM-driven trajectory control strategy, the *update time in advance* (in ms and as a percentage of the gait cycle) is determined by Equation 6.2, in which $T_{critical}$ is the critical instant; (ii) $T_{prediction}$ is the instant in which the LM decoding tool performed a classification; and (iii) *latency* is the time required by the control to change the assistance trajectory according to the predicted LM. For the SmartOs system, the *latency* value is around 260 ± 0.27 ms [2]. The *update time in advance* was computed and averaged for six transitions: St-LGW, LGW-St, LGW-SD, SD-LGW, LGW-SA, and SA-LGW. It represents the time prior to the critical instant when the AO was able to update its trajectory to adapt the assistance to the predicted LM.

$$Update\ time\ in\ advance\ (ms) = T_{critical} - (T_{prediction} + latency) \quad (6.2)$$

In addition, the real-time performance of the LM decoding was also assessed through the ACC, MCC, and F1-score.

6.2.3 RESULTS AND DISCUSSION

A. Analyzing the performance of the LM decoding tool

A total of **509,394 predictions were made during real-time experiments** with able-bodied participants walking with the SmartOs system operating under the proposed LM-driven trajectory control. Table 6.1 shows the average and standard deviation of the computed metrics (ACC, MCC, and F1-score) across different walking speeds and scenarios. Overall, the results show a **high average (above 0.961)** and **low standard deviation (below 0.004)** for the three metrics, with average ACC, MCC, and F1-score of 0.988 ± 0.001 , 0.969 ± 0.004 , and 0.977 ± 0.003 , respectively. These results advance the ones proposed in studies [40], [42], [43], [116], [117] since none of these studies demonstrated robust generalization to the preferred speeds of neurologically impaired users (below 2.7 km/h) when using a wearable assistive device operating under an active control mode.

Additionally, the achieved results are consistent with those obtained in Chapter 5 when able-bodied and stroke users walked with the SmartOs system operating under zero-torque control (average ACC, MCC, and F1-score of 0.986 ± 0.004 , 0.964 ± 0.010 , and 0.973 ± 0.005 , respectively). This consistency indicates that **the proposed LM decoding tool is robust across different speeds** (controlled and self-selected), **scenarios** (indoor and outdoor, with variable stair dimensions), **and control modes** (zero-torque and LM-driven trajectory controls), as the metrics for each speed, scenario, and assistance mode are quite similar.

Table 6.1 – Online test metrics for able-bodied participants

Scenario	Gait Speed (km/h)	ACC	MCC	F1-score
1	1.0	0.988	0.972	0.977
	1.2	0.988	0.968	0.976
	1.4	0.990	0.974	0.981
	1.6	0.988	0.967	0.976
2	1.0	0.989	0.970	0.978
	1.2	0.988	0.970	0.976
	1.4	0.989	0.969	0.978
	1.6	0.986	0.961	0.972
3	1.0	0.988	0.969	0.977
	1.2	0.991	0.976	0.982

Scenario	Gait Speed (km/h)	ACC	MCC	F1-score
	1.4	0.989	0.970	0.978
	1.6	0.986	0.964	0.973
Average $\pm$ STD		0.988 $\pm$ 0.001	0.969 $\pm$ 0.004	0.977 $\pm$ 0.003

B. Analyzing the performance of the LM-driven trajectory control

Table 6.2 summarises the *update time in advance* in milliseconds and as a percentage of the gait cycle. According to the results in Table 6.2, the **St-LGW transition** was detected and assisted earliest, with an average ***update time in advance* of 626 ± 242 ms**, representing $81.8 \pm 7.98\%$ of the previous gait cycle. In contrast, the **LGW-St transition** had the shortest *update time in advance* with an average of **80 ± 352 ms** or $97.8 \pm 13.6\%$ of the previous gait cycle. These results are also in line with those achieved in Chapter 5. The ability to early predict and assist the St-LGW transition may be explained by the possibility that subtle movements during the St task could signal the imminent onset of the LGW task. On the other hand, adapting the assistance of the SmartOs system during the LGW-St transition took the longest to be accomplished. The high standard deviation at this transition indicates that participants occasionally did not receive timely assistance from the SmartOs system, i.e. the assistance was adjusted after the critical instant. This may occur due to the fact that the LGW-St transition involves a more abrupt change by the user, making it difficult to predict.

Nonetheless, the results presented in Table 6.2 indicate that, on average, the SmartOs system was able to adapt its assistance during the swing phase once the trajectory of the next LM had been updated for **at least $81.8 \pm 7.98\%$ of the gait cycle** preceding the upcoming LM.

Table 6.2 – Average *update time in advance* in milliseconds (orange) and as a percentage of the gait cycle (blue)

St to LGW	LGW to SA	SA to LGW	LGW to SD	SD to LGW	LGW to St	Average $\pm$ STD
626 ± 242	302 ± 237	268 ± 275	319 ± 288	163 ± 221	80 ± 352	295 ± 170
81.8 ± 7.98	90.7 ± 8.22	92.3 ± 8.48	91.8 ± 6.16	94.2 ± 6.88	97.8 ± 13.6	91.4 ± 2.40

Figure 6.3 shows a graphical representation of the SmartOs performance during the LGW-SA transition. From Figure 6.3 – A to Figure 6.3 – C, the participant was in the stance phase of the

LGW task and the LM decoding tool classified “LGW”. In Figure 6.3 – D, the participant was in the swing phase, transitioning from the LGW task to the SA task. At this phase, it can be verified that the instant in which the LM decoding tool performed a new classification (“SA”) and the instant in which the SmartOs system adapted its assistance (Figure 6.3 – D) occurred before the critical instant (Figure 6.3 – E). It is noteworthy that the device updated its reference position trajectory according to the gait cycle phase. This means that, in the case of the LGW-SA transition, the reference position trajectory of the LGW task was updated to the swing phase of the reference position trajectory of the SA task, as depicted in Figure 6.3 – D. In this context, the reference position trajectory at the heel-strike of the upcoming LM (Figure 6.3 – E) was already the trajectory of the SA task.

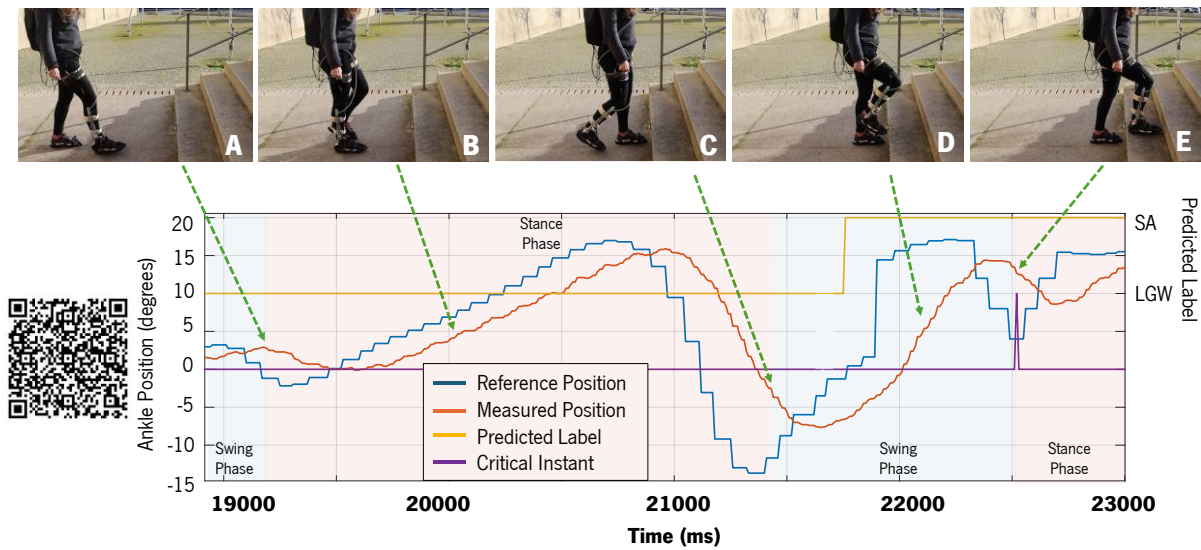


Figure 6.3 – Real-time operation of the LM-driven trajectory control. *A* and *E* represent the heel-strike; *B* represents the mid-stance; *C* represents the terminal stance; and *D* represents the mid-swing.

Overall, the achieved results advance the ones presented in the studies [40], [42], [43], [116], [117] since **the proposed LM-driven trajectory control demonstrated the ability to timely adapt the SmartOs’ assistance across six transitions** (St-LGW, LGW-St, LGW-SD, SD-LGW, LGW-SA, and SA-LGW) with an **average update time in advance of 295 ± 170 ms**, i.e., at $91.4 \pm 2.40\%$ of the gait cycle preceding the new LM.

Although the proposed LM-driven trajectory control showed promising results in both able-bodied participants, at speeds ranging from 1.0 to 1.6 km/h, and in different scenarios (indoor and outdoor), there are still opportunities for improvement. Specifically, there is a need to (i) conduct additional real-time validation procedures with more participants, including both able-bodied individuals and those with varying degrees of neurological impairments; (ii) extend the decoding

capabilities to other LMs, particularly RA and RD, and transitions; and (iii) increase the *update time in advance* for LGW-St transition.

6.3 ASSIST-AS-NEEDED ELECTROMYOGRAPHY-BASED CONTROL

6.3.1 CRITICAL ANALYSIS OF RELATED WORK

In the last years, EMG-based torque control strategies have been suggested to promote a smoother use of wearable assistive devices [139]. At this level, various EMG-based torque control strategies, typically based on a threshold [140], proportional [141], or Hill-type muscle model approaches [142], were proposed to foster the patient's participation while using wearable assistive devices. In EMG-based torque controls based on threshold methods, also known as EMG-triggered controllers, the assistance of the assistive device is triggered when EMG signals achieve certain threshold values. Apart from the intra- and inter-subject threshold dependence, this method does not allow continuous control to be achieved, as it only provides assistance when the threshold values are reached [37]. To solve that, both proportional controls and those based on Hill-type models have been proposed by building linear and non-linear models, respectively, by correlating EMG signals with joint torques [141]–[143]. However, in proportional control, the amount of gain required is found by trial-and-error experiments, which may result in time-consuming and inaccurate control. On the other hand, the Hill-type models (i) depend on muscle-specific parameters that are difficult to measure; (ii) present numerical instability issues; and (iii) are time-consuming, which may hinder their real-time application [142], [144]. Additionally, despite being a valuable contribution to muscle strengthening, neither of these EMG-based torque controls considers different levels of motor disabilities. The EMG-based control strategies provide assistance according to the patient's level of muscle strength. When applied to patients with low strength, these strategies provide proportionally little assistance. As such, they do not assist the patient with the level of strength needed to perform movements such as walking [32].

AAN EMG-based control strategies have been proposed to provide the robotic assistance required for users to complete a motion while considering their motor disabilities and invoking their participation [28], [32]–[38], [145]. For that, torque control loops are adopted, in which the user's joint torque is commonly estimated based on EMG signals, while reference joint torques are set according to assistance ratios [28], [32]–[38], [145]. Nonetheless, most of the already proposed AAN EMG-based control strategies (i) were developed for upper limbs [32]–[34];

(ii) depend on Hill-type models to estimate the user's joint torque, which may result in complex, user-dependent calibration, and time-consuming methods [28], [35], [36], [38], [145]; (iii) are not adaptable since they rely on fixed assistance ratios to define the desired joint torque trajectories [28], [38], [145]; and (iv) were not developed to assist the walking motion, but rather focus on isolated flexion and extension movements of the lower limb joints [28], [35]–[38].

This Ph.D. thesis tackles the above-mentioned limitations by proposing an AAN EMG-based control strategy to automatically assist the walking motion throughout the entire gait cycle. The system implements an **outer loop torque control and an inner loop position control, which adapts the level of assistance to be provided to the user in real-time and automatically**. To do this, the system presents two DL regressors: (i) one regressor to define user-oriented torque reference trajectories based on the user's body height, body mass, and gait speed [146], without the need for using fixed assistance ratios; and (ii) another regressor to determine the user's engagement (estimating the user's joint torque, in real-time, through a DL regressor fed by a fusion of kinematic, EMG, anthropometric, and demographic data [65]). The control strategy was designed, implemented, and validated into the SmartOs system to assist the ankle joint while considering the user's engagement.

6.3.2 METHODOLOGY

A. Hierarchical Control Architecture

The AAN EMG-based control proposed in this research follows a hierarchical architecture organized into high-, mid-, and low-levels, as depicted in Figure 6.4. It combines a torque outer loop and a position inner loop control. In this approach, **the outer loop introduces a "softening" effect in the human-robot interaction, while the inner loop ensures joint stiffness**. This helps suppress undesirable disturbances, eliminating the necessity for compensation based on anticipatory control models [27].

The high-level controller, implemented at 100 Hz, is responsible for (i) defining the human ankle joint reference angle ($\theta_{ref,h}$) and torque trajectories ($\mathcal{T}_{ref,h}$); (ii) estimating the human ankle joint torque trajectory ($\mathcal{T}_{est,h}$), in real-time, through the *Human-Torque Estimation* (HTE) block; and (iii) determine the variation of the $\mathcal{T}_{ref,h}$ and $\mathcal{T}_{est,h}$ ($\Delta\mathcal{T}_{ref,h}$ and $\Delta\mathcal{T}_{est,h}$ respectively). The $\theta_{ref,h}$ is generated by a regression model proposed in [147], considering the user's body height and gait speed. The methodology for defining $\mathcal{T}_{ref,h}$ is defined in sub-section *B. Estimation of Ankle Joint Reference Torque Trajectories*. In the proposed control strategy, the $\mathcal{T}_{ref,h}$ is defined according to the $\theta_{ref,h}$ and its

derivatives (angular velocity and angular acceleration), gait speed, anthropometric (body height and mass, shank, and foot lengths), and demographic (gender and age) data. The HTE block is explained in detail in sub-section *C. Estimation of Real-time Ankle Joint Torque Trajectories*. The HTE block estimates the $\mathcal{T}_{est,h}$ in less than 2 ms, considering the EMG signals from the *tibialis anterior* and *gastrocnemius lateralis* muscles (normalized by the corresponding MVCs), hip joint kinematics, walking speed, anthropometric (body height and mass, shank, and foot lengths), and demographic (gender, age) data.

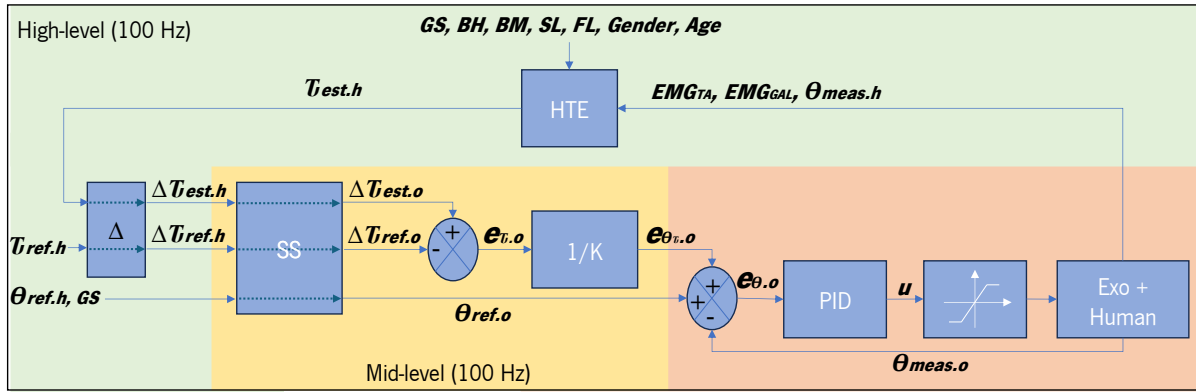


Figure 6.4 – AAN EMG-based torque control, combining a torque outer loop with a position inner loop. $\mathcal{T}_{ref,h}$ and $\mathcal{T}_{est,h}$ are the human ankle joint reference and estimated torques, respectively. $\Delta\mathcal{T}_{ref,h}$ and $\Delta\mathcal{T}_{est,h}$ are the variations of the $\mathcal{T}_{ref,h}$ and $\mathcal{T}_{est,h}$ respectively. $\Delta\mathcal{T}_{ref,o}$ and $\Delta\mathcal{T}_{est,o}$ are the $\Delta\mathcal{T}_{ref,h}$ and $\Delta\mathcal{T}_{est,h}$ interpolated to the low-level frequency, respectively. $e_{T,o}$ is the orthosis torque error between $\Delta\mathcal{T}_{ref,h}$ and $\Delta\mathcal{T}_{est,h}$. $\theta_{ref,h}$ and $\theta_{ref,o}$ are the human and orthosis ankle joint reference angles, respectively. $e_{\theta_{T,o}}$ is the orthosis torque-derived position error. $\theta_{meas,o}$ is the orthosis ankle joint measured angle. $e_{\theta,o}$ is the orthosis position error. u is the PID command. EMG_{TA} and EMG_{GAL} are the EMG signals measured from the *tibialis anterior* and *gastrocnemius lateralis* muscles, respectively. $\theta_{meas,h}$ is the human hip joint measured angle. GS is the gait speed. BH and BM are the human body height and mass, respectively. SL and FL are the shank and foot lengths, respectively. K is a fixed factor equal to 1.33 N.m/radians. SS is a speed scaling block achieved by Equation 6.1. PID is a Proportional-Integral-Derivative (PID) controller. HTE is a *Human-Torque Estimation* (HTE) block.

In the mid-level controller, which operates at 100 Hz, the human ankle joint reference angles ($\theta_{ref,h}$), $\Delta\mathcal{T}_{ref,h}$ and $\Delta\mathcal{T}_{est,h}$ are interpolated (achieving the orthosis ankle joint reference angles ($\theta_{ref,o}$), $\Delta\mathcal{T}_{ref,o}$ and $\Delta\mathcal{T}_{est,o}$ respectively) to the low-level control frequency through the *Speed Scaling* (SS) block (see Equation 6.1). The $\Delta\mathcal{T}_{ref,o}$ and $\Delta\mathcal{T}_{est,o}$ are compared, generating the orthosis torque error ($e_{T,o}$). The $e_{T,o}$ is converted into an orthosis torque-derived position error ($e_{\theta_{T,o}}$) through a fixed scaling

value K set at 1.33 N.m/radians. This value was empirically found for the used AO and it represents the rotational stiffness.

At the low-level controller (working at 1 kHz), it was empirically verified that was required to apply a feedforward position control to prevent the ankle orthosis from moving to positions that could cause injury to the user and could damage itself. This feedforward position control was also proposed in a study [27] to improve trajectory tracking. To this end, a feedforward position control was applied to the inner loop, adding the $\theta_{ref,o}$ that the orthosis should move to while taking into account the $\mathcal{T}_{ref,h}$ of the outer loop. The $e_{\theta_{ref,o}}$, $\theta_{ref,o}$ and the orthosis ankle joint measured angle ($\theta_{meas,o}$) are compared, generating the orthosis position error ($e_{\theta,o}$), fed to the PID controller. The PID controller was implemented using proportional, integral, and derivative gains of 95, 1.5, and 1.5, respectively. Considering the e_{θ} , the PID controller computes a PID command (u) that is limited to maximum and minimum values of 2500 and -2500, through a saturator. This command is interpreted by the ankle orthosis, generating the corresponding motor torque.

With this control architecture, it is intended that if the user performs (i) an ankle joint angle and torque trajectories **closer to the references, the assistance of the ankle orthosis should be minimal**; (ii) an ankle joint angle and/or torque trajectories **different from the references**, the **ankle orthosis should provide assistance in order to compensate for these differences**.

B. Estimation of Ankle Joint Reference Torque Trajectories

Since the proposed AAN EMG-based control strategy must follow a user-centered design, it was required that the AO provides assistance oriented to the user's needs. This may be achieved by defining a control reference variable, i.e., ankle joint torque, adapted to each user. In this connection, regressor-based DL models were trained to estimate ankle joint reference torque trajectories ($\mathcal{T}_{ref,h}$), according to the user's body height, body mass, and gait speed. In this Ph.D. thesis, the focus is given to CNN. Further details of estimating user-oriented torque reference trajectories with the LSTM model can be found in the study [146].

To train the DL models, a data collection was performed. The study involved thirteen able-bodied adult participants (6 males and 7 females) with an average age of 24.2 ± 1.85 years, an average body mass of 65.2 ± 10.3 kg, and an average body height of 168 ± 12.0 cm. Balanced gender distribution was tackled considering possible biomechanical gender differences [148]. Before

undergoing the experiments, each participant gave written and informed consent according to the ethical conduct of the University of Minho Committee (CEICVS 006/2020).

As depicted in Figure 6.5, participants were instrumented with a total of 12 pairs of retro-reflective markers, which combined with a twelve-camera motion-capture system (Oqus; Qualisys—Motion Capture System, Göteborg, Sweden) and five force platforms embedded on the floor (FP4060; Bertec, Ohio, OH, USA) were utilized to collect the lower limb joint angles and torques (at the ankle, knee, and hip joints). Moreover, it was studied how the use of EMG signals affects the ankle joint torque estimation. For that, an 8-channel surface EMG system [Trigno Avanti (Delsys Incorporated, Natick, USA)] was employed to collect EMG data from the *tibialis anterior*, *gastrocnemius lateralis*, *biceps femoris*, and *vastus lateralis* muscles.

Each subject was instructed to perform ten forward walking trials, walking sequentially at seven controlled walking speeds (1.0, 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 km/h). These speeds were controlled by a metronome and were chosen to cover the typical walking speeds of post-stroke patients and able-bodied users. The participants were asked to look ahead and walk naturally according to the beats of the metronome. Further details of the protocol are presented in [65], [121].

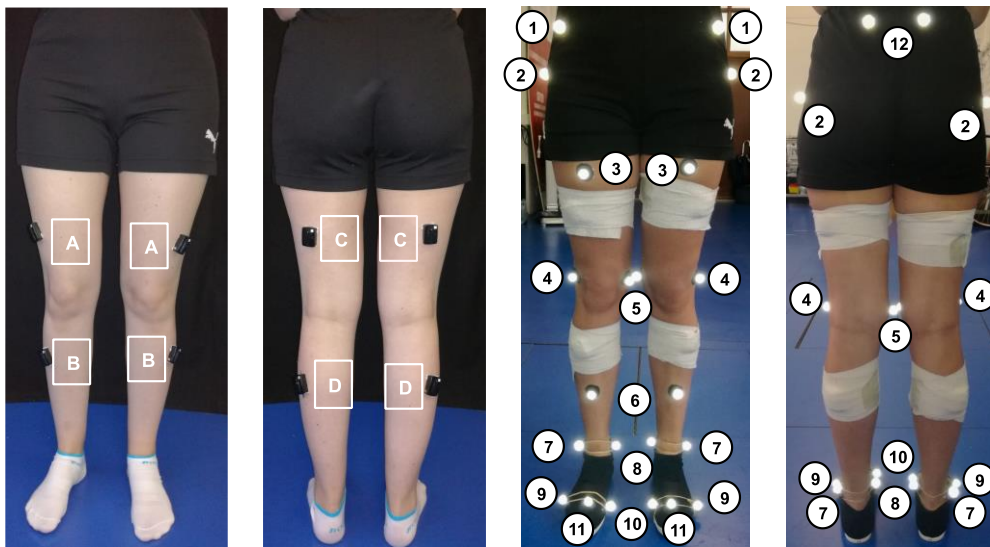


Figure 6.5 – EMG configuration and marker-set adopted: (A) *vastus lateralis*; (B) *tibialis anterior*; (C) *biceps femoris*; (D) *gastrocnemius lateralis*; (1) Anterior superior iliac spine; (2) trochanter; (3) thigh; (4) lateral knee; (5) medial knee; (6) shank; (7) lateral ankle; (8) medial ankle; (9) foot metatarsal 5; (10) foot metatarsal 1; (11) foot metatarsal 2; (12) posterior superior iliac spine.

Out of the thirteen participants, one was randomly selected to test the trained model. A LOSOCV method among the remaining twelve participants was implemented to evaluate the model

generalization and optimize the model hyperparameters. For the CNN, the parameters explored were (i) the kernel size (2×2 , 5×5 , and 10×10); (b) the number of filters per convolutional layer (8, 16, 32, 64); and (c) the number of convolutional layers (1, 2, 3). Further, an empirical analysis was applied to select (i) the normalization method (considering the max-min, z-score, and robust normalization methods); (ii) the optimal batch size; and (iii) the dropout percentage. In addition, both neural networks' weights and biases were updated according to an adaptive moment estimation optimization algorithm (ADAM) considering the mean square error (MSE) ([36,51]).

The regression model performance was evaluated during the LOSOCV and model testing procedures. Three metrics were determined, namely, r , R^2 , and the computational load (in milliseconds). The predictions performed by the trained model were also evaluated using the Bland–Altman Plot [151]. All predictions were performed in a Hewlett-Packard computer with an Intel® Core™ i7-4710MQ CPU @ 2.50 GHz processor and a Random Access Memory with 16.0 GB.

C. Estimation of Real-time Ankle Joint Torque Trajectories

Considering that the SmartOs system is not able to measure the human ankle joint torque, it was required to explore a methodology to estimate user-oriented ankle joint torque trajectories ($\mathcal{T}_{meas,h}$) in real-time, in a similar way as a torque sensor. In this connection, this Ph.D. thesis proposes the HTE block (Figure 6.4), which represents an EMG-based torque estimation DL regressor. For that, a CNN model was explored considering the following data fusion: gait speed, kinematic (hip kinematics), EMG (*tibialis anterior* and *gastrocnemius lateralis* muscles), anthropometric (body height and mass, ranging from 1.50 to 1.90 m and 50.0 to 90.0 kg, respectively, and shank and foot lengths) and demographic data (age, gender). Further details can be found in the study [65].

The CNN model was trained with a walking dataset collected from seventeen healthy participants (9 females and 8 males) with a mean body height of 168.0 ± 10.31 cm, a mean body mass of 70.11 ± 14.26 kg, and a mean age of 28.05 ± 3.66 years.

Participants were instrumented with (i) an 8-channel surface EMG system [Trigno Avanti (Delsys Incorporated, Natick, USA)] to collect EMG data from the *tibialis anterior*, *gastrocnemius lateralis*, *biceps femoris*, and *vastus lateralis* muscles; (ii) a total of 12 pairs of retro-reflective markers, in which combined with a twelve-camera motion-capture system (Oqus; Qualisys—Motion Capture System, Göteborg, Sweden) and Force Plate-Instrumented Treadmill (Side-by-Side Treadmill – AMTI, MA, USA) were used to acquire the lower limb joint angles and torques (at the ankle, knee,

and hip joints). After, each participant was instructed to walk for 4 minutes on the instrumented treadmill, performing 2 minutes at 1.5 km/h and then 2 minutes at 2 km/h.

An empirical analysis was conducted to select (i) the kernel size (2, 10, 20, 40, 60); (ii) the number of convolutional layers (1, 2, 3, 4); (iii) the number of filters per convolutional layer (8, 16, 32, 64, 128); (iv) the sequence length (40, 50, 60, 80, 100, 120, 150); (v) the batch size; and (vi) the dropout rate. The normalization method was also studied among max-min, z-score, and robust normalization methods. Furthermore, the ADAM algorithm based on the MSE was used to update the weights and biases of the CNN. This empirical analysis was conducted through the LOSOCV procedure. Of the seventeen participants, one (female 27 years old and a body mass and height of 73.4 kg and 1.63 m, respectively) was randomly selected to test the model. Thus, the model was trained with data from 16 subjects.

Three evaluation metrics were employed to evaluate the offline CNN's performance, namely, the RMSE, the Normalized Mean Square Error (NMSE), and the r . These metrics were computed between the predicted and the real (ground truth) ankle joint torque trajectories during the LOSOCV and the model testing procedures (both performed in a Hewlett-Packard computer with an Intel® Core™ i7-4710MQ CPU @ 2.50 GHz processor and a Random Access Memory with 16.0 GB).

Further, an experimental protocol was performed to evaluate the real-time performance, i.e., the prediction time of the CNN into SmartOs CCU. This protocol involved one able-bodied male participant (27 years old) with a body height of 1.70 m and a body mass of 81.2 kg. In the beginning, the participant's gender, age, body mass, height, leg length, and foot length were measured and introduced in the mobile graphical application of the SmartOs system. Then, the participant performed two MVCs for each muscle to normalize the EMG data. After that, the participant was instructed to perform a 5-seconds standing calibration trial for calibrating the InertialLab system. At last, the participant walked on the instrumented treadmill for 5 minutes at 1.5 km/h, while the ankle joint torque trajectories were estimated in real-time.

C. Experimental Validation of AAN EMG-based Control

To validate the complete AAN EMG-based control proposed in Figure 6.4, five healthy participants (3 males and 2 females with an average age, body height, and body mass of 27.8 ± 3.1 , 170.4 ± 8.2 , and 67.8 ± 11.4 , respectively) without evidence of motor disorders were involved. All participants provided informed consent according to the University of Minho Ethics Committee

(CEICVS 006/2020). It is important to note that these participants were not involved in training the regressors described in sub-sections *B* and *C*.

The protocol started by collecting the participant's gender, age, body height and mass, and foot and shank lengths. Then, participants were equipped with (i) two EMG sensors placed on the right *tibialis anterior* and the right *gastrocnemius lateralis* muscles, following the SENIAM recommendations [105]; and (ii) 2 IMUs from the InertialLab system positioned in the pelvis and in the right thigh, to collect hip joint angles. All these data are used in the HTE block, as depicted in Figure 6.4. Once instrumented with the sensor systems, the participant performed two MVCs per muscle. After that, the participant was instrumented with the SmartOs system (Figure 6.6).

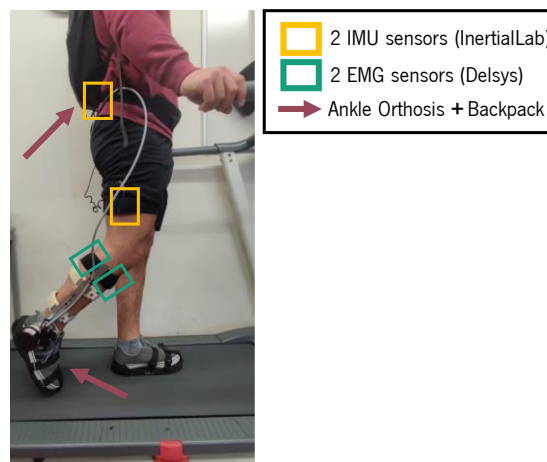


Figure 6.6 – Male participant equipped with the InertialLab, Trigno Avanti, and SmartOs systems.

Once instrumented, participants underwent a period of familiarization with the device following a trajectory-tracking position control. After familiarization, the data collection started with participants walking in two different sessions. One session consisted of participants being assisted by the AO following a **trajectory-tracking position control**. The other session consisted of participants being assisted by the AO following an **AAN EMG-based control**. Both sessions were performed at three speeds (1.2, 1.4, and 1.6 km/h). However, the participants did not know which control strategy was controlling the AO in order to evaluate the users' perception of which strategy was more or less adapted to their real-time motion. In this connection, a researcher randomly selected the assistive control strategy. Subsequently, participants performed three tasks. In the first, they were asked to remain in a standing position with their right leg raised (the leg instrumented with the SmartOs system), with no movement, for 20 seconds. Secondly, participants were asked to walk for 1 minute on the treadmill, which was initially set at a speed of 1.2 km/h. This task is referred to as the *unconditioned task*, in which participants were asked to actively perform the walking motion. In the

third test, the participants were asked to lean on the sidebars of the treadmill, so that they were almost suspended (only their feet touched the treadmill mat, but without supporting their body) for 1 minute. At this point, participants were asked to simulate a pathological condition by trying not to activate the *tibialis anterior* and *gastrocnemius lateralis* muscles to perform the gait. In other words, participants had to let the AO do most of the walking motion. Thus, this task is referred to as the *conditioned task*, in which participants were asked to passively perform the walking motion. Given this condition, it would be expected that there would be a decrease in the activation of the aforementioned muscles and, consequently, the AO would increase its assistance when guided by an AAN EMG-based control. When guided by a trajectory-tracking position control, it would be expected that the assistance provided by the AO during both *conditioned* and *unconditioned* tasks would be identical, since this control strategy does not consider the user's participation. After completing these three tasks, participants performed the same continuous tasks at the same gait speed (1.2 km/h) for the second assistive control strategy.

After performing the two sessions (i.e., walking under the trajectory-tracking position control and AAN EMG-based control in random order), participants were given a four-question open questionnaire with the following questions:

1. Among the tasks performed, which condition provided more variable assistance?
2. Among the tasks performed, which condition provided more adequate assistance?
3. Considering the task of walking suspended from the sidebars, in which condition did you feel that the orthosis provided more assistance?
4. Considering the possibility of fatigue, which condition would you choose for prolonged use of the AO?

After answering the questions, the protocol was repeated for the remaining speeds, i.e., 1.4 and 1.6 km/h.

6.3.3 RESULTS AND DISCUSSION

A. Estimation of Ankle Joint Reference Torque Trajectories

In this Ph.D. thesis, it is presented a proof-of-concept of DL regressors' applicability to achieve an accurate and generalized method for estimating user-oriented ankle torque trajectories for the entire gait cycle, considering gait speeds ranging from 1.0 to 4.0 km/h and for individuals with body

height and mass varying from 1.51 to 1.83, and from 52.0 to 83.7 kg, respectively. This enables the estimation of ankle joint reference torque trajectories for a widespread population, including SmartOs' users.

Table 6.3 presents the best results achieved for the DL-based regressor algorithm, for both validation and test conditions, when considering/not considering the EMG signals as input. Pursuing the hypothesis that the ankle joint torque trajectories can be accurately estimated without using EMG signals, a statistical analysis was conducted to evaluate possible significant differences. The Shapiro–Wilk normality test showed that all data were parametric, and the assumptions of homoscedasticity and the existence of outliers were accomplished. Thus, a two-tailed and paired t test was conducted with a level of confidence of 95%. The results indicate that there were no significant differences between both approaches, with a p -value > 0.05 having been achieved for all metrics (r : p -value = 0.17, and R^2 : p -value = 0.28). Since the p -values were greater than 0.05 for all metrics, it is concluded that there were no significant differences between the two CNN models. This suggests that the **CNN model can estimate ankle joint reference torque trajectories accurately even without using EMG signals.**

The best parameters found for the CNN were the following: (i) kernel size: 2x2; (ii) number of convolutional layers: 2; (iii) number of filters: 8 and 16 in the first and second convolutional layers, respectively; (iv) normalization method: robust; (v) batch size: 20; and (vi) dropout: 25%.

Table 6.3 – DL models performance when EMG signals were/were not included as inputs

Inputs	Deep Learning Model	r		R^2		Prediction Time (ms/sample)
		LOSOCV	Test	LOSOCV	Test	
Body height, mass, gait speed, and ankle joint angles	CNN	0.89 $\pm$ 0.03	0.92	0.91 $\pm$ 0.03	0.94	0.51
Body height, mass, gait speed, ankle joint angles, and EMG from <i>tibialis anterior</i> and <i>gastrocnemius lateralis</i>		0.90 $\pm$ 0.04	0.89	0.92 $\pm$ 0.04	0.92	0.78

Given its prominent capacity to estimate the ankle joint torque trajectories, the predictions performed by CNN were compared to the real ankle joint torque trajectories of the test dataset using the Bland–Altman Plot. The results depicted in Figure 6.7 – a) show that the predictions made by CNN are closer to the real ankle joint torque trajectories since the majority of the measures are

within the limits of agreement, the bias is close to 0 N.m, and the limits of agreement are small. Furthermore, Figure 6.7 – b) illustrates the average and standard deviation values of the real and CNN-based predicted ankle joint torque for the test dataset. These results show that the **CNN produced reference ankle joint torque trajectories closely similar to the real ones.**

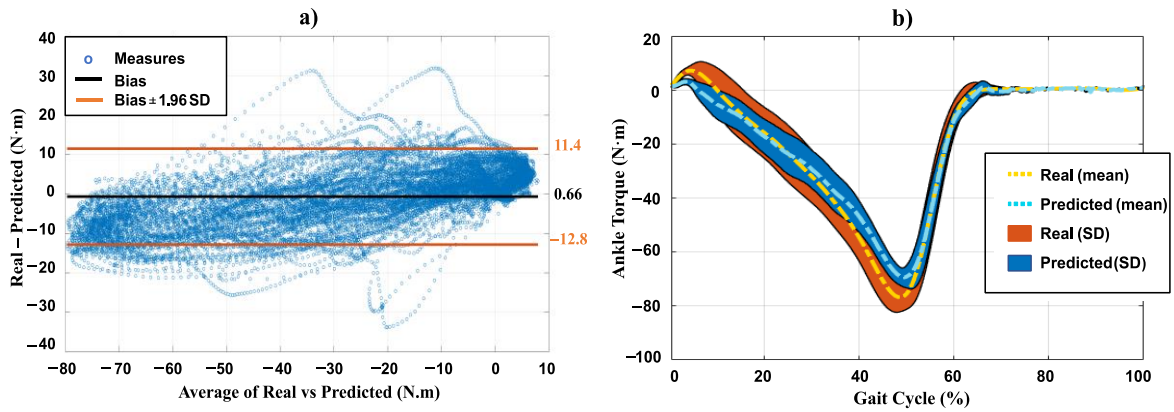


Figure 6.7 – **(a)** Bland–Altman plot results; **(b)** Average (dashed lines) and standard deviation (SD) (filled area) of the real and CNN-based predicted ankle joint torque for the test dataset.

The achieved results were encouraging when considering the findings presented in previous studies [152]–[156]. The study [152] reached an R^2 of 0.48 for predicting the peak ankle dorsiflexion torque using linear and quadratic equations. The study [153] estimated ankle, knee, and hip angles and torques for the stance phase using feedforward and LSTM neural networks, revealing a r of 0.98. In the study [154], peak ankle, knee, and hip joint angles and torques were estimated using linear, quadratic second-order, and quadratic third-order equations. The highest value of R^2 for peak ankle joint torque estimation was 0.93. Other studies [155], [156] have reported that a Multilayer Perceptron can estimate knee joint torque trajectories with an r of 0.97 by combining EMG signals with kinematic sensors.

Despite presenting different datasets and study conditions, the CNN tool proposed by this research presents an estimation performance in line with the studies [152]–[156], by predicting ankle joint torque trajectories for the entire gait cycle with an R^2 of 0.91 ± 0.03 (r of 0.95 ± 0.18). The tool developed in this thesis advances by estimating torque for the complete gait cycle, which is advantageous over the estimation for specific gait events [152]–[156] because the torque curve is characterized not only in magnitude but also temporally [157]. Further, **the proposed tool predicts ankle joint torque trajectories without the need for complex data acquisitions related to EMG** [155], [156].

Moreover, **the low computational load demonstrated by CNN highlights its potential for real-time conditions**. These findings revealed that the proposed kinematic-, speed-, and anthropometry-dependent approach corresponds to **a practical solution to estimate reference torque trajectories for assistive control strategies**.

B. Estimation of Real-time Ankle Joint Torque Trajectories

This section presents the results of the HTE block presented in Figure 6.4. It demonstrates the proof-of-concept for using DL regressors to achieve a generalized estimation of user-oriented ankle joint torque, in real-time. The applicability of these regressors was tested under two slow walking speeds, namely 1.5 and 2.0 km/h, and for participants with varying body height (from 1.50 to 1.90 m) and mass (from 50.0 to 90.0 kg). Consequently, this method enables the estimation of ankle joint torque trajectories covering the mean anthropometric data across countries and the preferred walking speeds of post-stroke patients.

Table 6.4 presents the best results achieved during the LOSOCV method. In Table 6.4, two types of results are presented: results for torque estimation using (i) EMG, anthropometric, demographic, and speed data; and (ii) EMG, anthropometric, demographic, speed, and kinematic data (joint angle, angular velocity, and angular acceleration of the sagittal plane), testing knee and hip kinematic data. The ankle kinematics were not considered because it is affected by the motion of the active ankle orthosis, i.e., the ankle kinematics could result from the human and/or robot motion. Thus, the user's ankle joint torque estimation might be jeopardized.

Considering the different combinations of input data, the results of Table 6.4 suggests that the **CNN achieved high generalization ability**, characterized by the high average and low standard deviation values for all evaluation metrics **when EMG, anthropometric demographic, speed, and hip kinematic data were used as input**. Taking into account this combination of inputs, the number of convolutional layers was studied since these layers have a strong impact not only on the performance of the model but also on the prediction time [158].

Table 6.4 – RMSE, NMSE, and r metrics for LOSOCV procedure

Input data	RMSE (N.m)	NMSE	r
EMG, anthropometric, demographic, and speed data	23.2 ± 8.35	0.602 ± 0.615	0.703 ± 0.242

Input data	RMSE (N.m)	NMSE	<i>r</i>
EMG, anthropometric, knee kinematics, demographic, and speed data	22.4 ± 9.79	0.492 ± 0.391	0.790 ± 0.092
EMG, anthropometric, hip kinematics, demographic, and speed data	20.2 ± 4.44	0.390 ± 0.267	0.802 ± 0.054

Table 6.5 exhibits the CNN performance for both LOSOCV and testing procedures when varying the number of convolutional layers. LOSOCV results pointed out that CNN performance reduces as fewer convolutional layers are employed. However, different results were achieved for the testing procedure, **where the CNN reached the best performance when only two convolutional layers were used**. For that model, the real and the predicted joint torques of the test dataset were graphically analyzed, depicted in Figure 6.8. Based on Figure 6.8, a high level of similarity between the monotony of both curves is reached, confirmed by the *r* value (0.846). From Table 6.5 and Figure 6.8, it is verified that the RMSE values (slightly above 20 N.m) are associated with the fact that the model cannot achieve the maximum signal magnitude. The obtained results are in line with the expected. The study [155] predicted the isokinetic torques for the knee joint, achieving RMSE values between 26.8 and 29.0 N.m. The proposed tool estimates the ankle joint torque for the entire gait cycle point-by-point with lower RMSE values (23.4 ± 8.36 N.m). In the study [152], the peak ankle joint dorsiflexion torque using linear and quadratic equations achieves a *r* of 0.69. In this Ph.D. thesis, the best model presented a *r* value of 0.86 ± 0.23 for the entire gait cycle.

Table 6.5 – RMSE, NMSE, and *r* during the LOSOCV and model test procedures

Input data	Convolutional Layers (Filters)	RMSE (N.m)		NMSE		<i>r</i>	
		LOSOCV	Test	LOSOCV	Test	LOSOCV	Test
EMG, anthropometric, demographic, and speed data	4 (16, 32, 64, 128)	20.2 ± 4.44	27.0	0.390 ± 0.267	0.454	0.802 ± 0.054	0.857

Input data	Convolutional Layers (Filters)	RMSE (N.m)		NMSE		<i>r</i>	
		LOSOCV	Test	LOSOCV	Test	LOSOCV	Test
EMG, anthropometric, knee kinematics, demographic, and speed data	3 (16, 32, 64)	21.4 ± 4.74	27.2	0.469 ± 0.323	0.459	0.781 ± 0.062	0.841
EMG, anthropometric, hip kinematics, demographic, and speed data	2 (16, 32)	23.4 ± 8.36	20.5	0.494 ± 0.299	0.261	0.754 ± 0.105	0.846

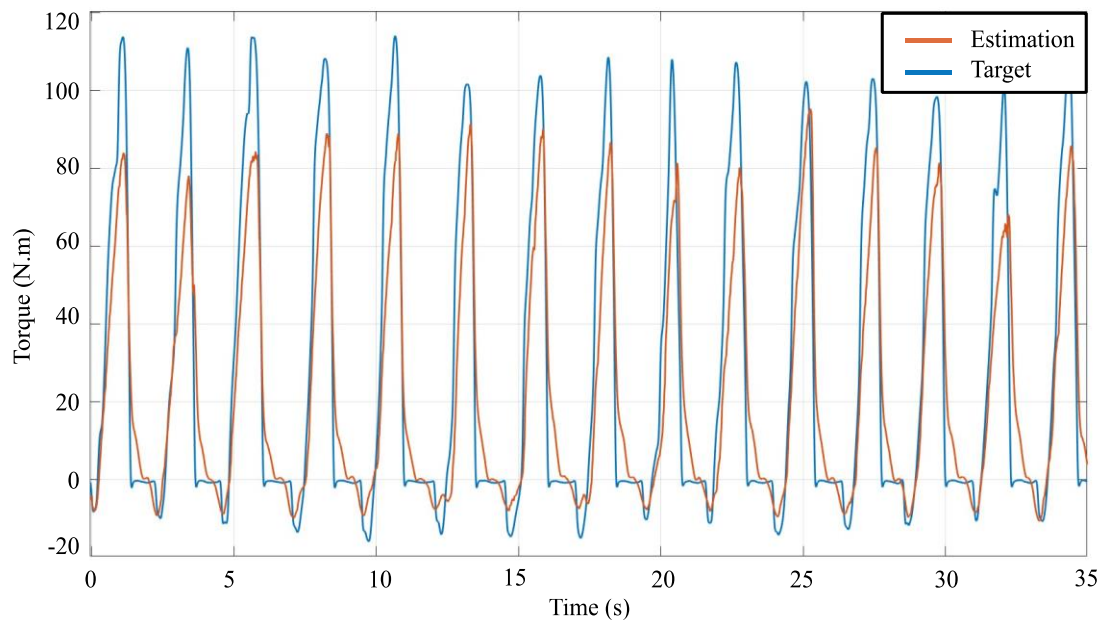


Figure 6.8 – Real and predicted ankle torques for the test subject (female 27 years old, body mass and height of 73.4 kg and 1.63 m, respectively), using a CNN with 2 convolutional layers.

To complete the CNN model evaluation, the computational load of the three CNN architectures (with 2, 3, and 4 convolutional layers) was assessed in the real experiments, into the SmartOs' CCU. Results presented in Table 6.6 show that there is a high difference in the computational load when the number of convolutional layers varies, achieving **the lowest time (2 ms) when two convolutional layers are used**. Since the high-level of the SmartOs system works at 100 Hz, i.e., every 10 ms, the torque estimation performed by the CNN architecture with two convolutional layers

is the only one that complies with that operating frequency. This result overcomes the one presented in the study [159], reporting 63 ms to estimate the knee joint torque using a musculoskeletal model.

Once integrated into the SmartOs system, the DL regressor was tested during real-time procedures. Figure 6.9 presents the real-time estimation of ankle joint torques along with the ankle joint angle recorded by the InertialLab system, and the EMG signals of *tibialis anterior* and *gastrocnemius lateralis* recorded by the Trigno Avanti system. Based on Figure 6.9, it is possible to infer that the ankle joint torque pattern (magnitude and shape) estimated by the HTE block is similar to the one presented in Figure 6.8.

Table 6.6 – CNN's computational load

Input Data	Convolutional Layers (Filters)	Computational Load (ms/sample)
EMG, anthropometric, demographic, speed, and hip kinematics data	4 (16, 32, 64, 128)	42
	3 (16, 32, 64)	29
	2 (16, 32)	2

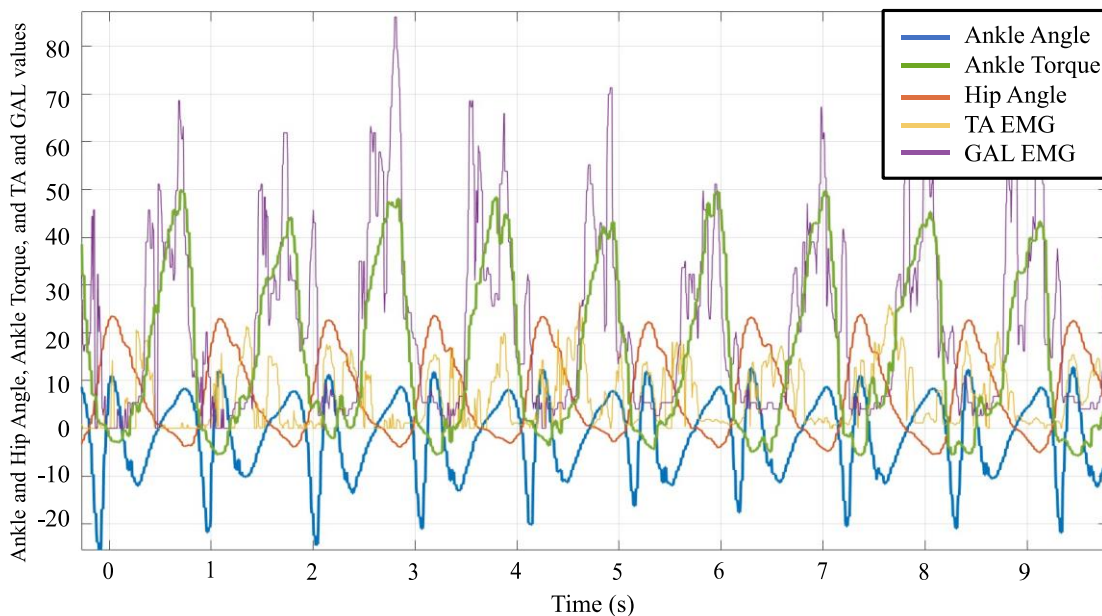


Figure 6.9 – Ankle and hip joint angles (in degrees, InertialLab), EMG data (as a percentage of MVC) from *tibialis anterior* (TA) and *gastrocnemius lateralis* (GAL) (Trigno Avanti), and ankle joint torque (in N.m) estimated in the SmartOs system, using a CNN with 2 convolutional layers.

The contributions to the state-of-the-art focused on proposing a tool to estimate ankle joint torque point-by-point during the AO-assisted walking motion without relying on (i) complex mathematical models that take too long to provide usable torques for exoskeleton control; (ii) force platforms that are limited to motion analysis labs; (iii) torque sensors, commonly not used in wearable assistive devices given their obtrusive design; and (iv) muscle-specific parameters that are difficult to measure. The proposed DL-based tool was able to estimate joint torque in 2 ms. The achieved outcomes proved that the **proposed tool can be implemented and efficiently work into the high-level of a wearable assistive device (in this case, the SmartOs system) with a low computational burden**, which enables its use to control the AO in real-time.

C. AAN EMG-based Control

To analyze the contributions of the proposed AAN EMG-based control strategy, several variables were analyzed between the *conditioned* and *unconditioned* tasks, namely: (i) EMG signals of the *tibialis anterior* and *gastrocnemius lateralis*; (ii) range of motion of the hip joint; (iii) human ankle joint torque; (iv) orthosis motor torque; and (v) the human ankle joint angle. Table 6.7 shows the variation of the EMG signals from *tibialis anterior* and *gastrocnemius lateralis*, the range of motion of the hip joint, and human ankle joint torque between *unconditioned* and *conditioned* tasks during AAN EMG-based control strategy. **A negative sign indicates that the variable in question showed a decrease during the *conditioned* task** compared to the values of the same variable measured during the *unconditioned* task.

According to Table 6.7, it is possible to verify that, at the *conditioned task*, the activation of the ***tibialis anterior* and *gastrocnemius lateralis* muscles decreased**, on average, $32.1\% \pm 23.2\%$ and $45.4\% \pm 21.0\%$, respectively, across all participants and gait speeds. **The same behavior was verified for the hip joint**, in which a reduction of $22.9\% \pm 11.9\%$ was verified in the range of motion of the hip joint. At last, the **human ankle joint torque also decreased by $11.3\% \pm 5.7\%$, on average**. These results reflected that, **at the *conditioned* task, participants have reduced their active participation in performing the walking motion**, as expected. An example of a graphical visualization of these differences is presented in Figure 6.10.

As a consequence, to complete the walking motion, the SmartOs orthosis **increased its contribution** across all participants and gait speeds. According to Table 6.8, the **dorsiflexion motor torque** (i.e., the positive motor torque values) **increased by $9.9\% \pm 6.6\%$, on average**. On the other hand, the **plantar flexion motor torque** (i.e., the negative motor torque values)

increased by $9.7\% \pm 4.8\%$, on average. These results are in line with what would be expected, as, in the *conditioned* task, participants were not actively involved in the execution of the walking motion. Consequently, their EMG signals were close to the minimum values, resulting in a lower human ankle joint torque. It is therefore expected that the AO is responsible for the execution of the gait movement, as evidenced by the increase in motor torque. Figure 6.10 depicts the motor torque increase during the *conditioned* task.

Additionally, as depicted in Figure 6.10, the maximum dorsiflexion and plantar flexion ankle angles that participants were asked to perform were set at 12.0° and -11.0° , respectively. Due to the increased assistance provided by the AO, the maximum dorsiflexion and plantar flexion angles measured during the *conditioned* task were $12.7^\circ \pm 0.83^\circ$ and $-7.7^\circ \pm 0.59^\circ$, respectively. From Figure 6.10, it can be seen that the **ankle joint angle trajectories during the *conditioned* task were close to that achieved during the *unconditioned* task**, indicating that the AO ensured that the ankle joint pattern was accomplished during the participants' quasi-passive participation.

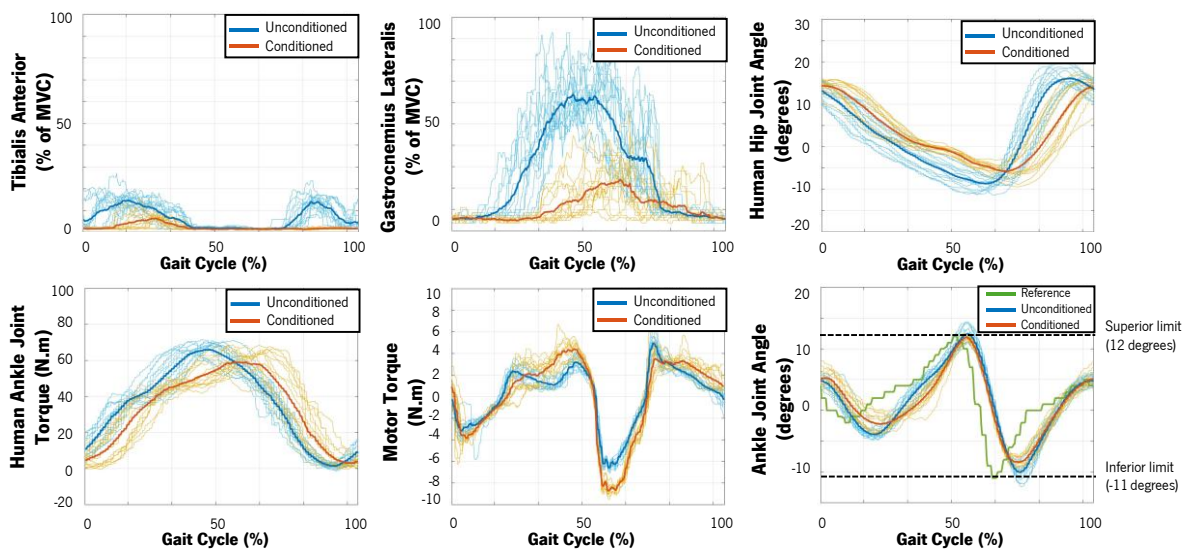


Figure 6.10 – AAN EMG-based control results of Participant 2. Averaged gait cycles during two conditions: *unconditioned* task (blue color) and *conditioned* task (orange color). Representation of the *tibialis anterior* signals, *gastrocnemius lateralis* signals, human hip joint angles, human ankle joint torques, motor torque, and ankle joint angles.

Table 6.7 – Variation of the EMG signals from *tibialis anterior* and *gastrocnemius lateralis*, range of motion (ROM) of the hip joint, and human ankle joint torque between *unconditioned* and *conditioned* tasks during AAN EMG-based control strategy (a negative and a positive sign means a reduction and an increase, respectively, when comparing the variable measured at the *conditioned* task to the *unconditioned* task)

ID	EMG from <i>tibialis anterior</i>			EMG from <i>gastrocnemius lateralis</i>			Hip ROM			Human torque		
	1.6 km/h	1.4 km/h	1.2 km/h	1.6 km/h	1.4 km/h	1.2 km/h	1.6 km/h	1.4 km/h	1.2 km/h	1.6 km/h	1.4 km/h	1.2 km/h
1	-29.7%	-32.0%	-33.5%	-70.5%	-64.7%	-57.3%	-22.7%	-24.7%	-16,1%	-14.3%	-15.0%	-14.4%
2	-63.1%	-64.5%	-63.0%	-67.1%	-62.6%	-59.8%	-4.9%	-18.6%	-1,0%	-14.0%	-11.0%	-5.8%
3	-55.7%	-63.4%	-32.0%	-22.2%	-9.4%	-11.1%	-22.0%	-17.8%	-22,8%	-16.3%	-22.7%	-20.1%
4	-1.8%	-2.0%	-16.0%	-48.9%	-18.9%	-26.8%	-48.8%	-44.3%	-38,0%	-7.0%	-9.3%	-1.2%
5	-1.7%	-9.3%	-14.2%	-37.3%	-64.5%	-59.8%	-22.8%	-21.3%	-17,6%	-3.4%	-6.7%	-8.9%
Average ± STD/Speed	-30.4% ± 25.9%	-34.2% ± 26.2%	-31.7% ± 17.5%	-49.2% ± 18.2%	-44.0% ± 24.6%	-42.9% ± 20.3%	-24.2% ± 14.1%	-25.3% ± 9.8%	-19,1% ± 11,9%	-11.0% ± 4.9%	-12.9% ± 5.6%	-10.1% ± 6.6%
Total average ± STD	-32.1% ± 23.2%			-45.4% ± 21.0%			-22.9% ± 11.9%			-11.3% ± 5.7%		

Table 6.8 – Variation of the dorsiflexion and plantar flexion motor torques between *unconditioned* and *conditioned* tasks (a negative and a positive sign means a reduction and an increase, respectively, when comparing the variable measured at the *conditioned* task to the *unconditioned* task). Maximum dorsiflexion, and plantar flexion angles measured at the *conditioned* task

ID	Dorsiflexion Motor Torque			Plantar Flexion Motor Torque			Maximum Dorsiflexion Angle (°)			Maximum Plantar Flexion Angle (°)		
	1.6 km/h	1.4 km/h	1.2 km/h	1.6 km/h	1.4 km/h	1.2 km/h	1.6 km/h	1.4 km/h	1.2 km/h	1.6 km/h	1.4 km/h	1.2 km/h
1	18.4%	10.4%	8.1%	11.6%	10.9%	10.5%	11.2	11.8	12.6	-6.3	-8.1	-7.6
2	6.1%	6.9%	6.9%	11.4%	12.3%	17.6%	10.4	11.9	12.9	-7.4	-7.1	-7.4
3	16.9%	1.8%	1.4%	8.7%	1.2%	3.8%	12.7	13.8	14.6	-6.9	-7.9	-7.9
4	12.9%	26.8%	14.5%	11.0%	21.6%	5.9%	11.4	13.8	13.4	-8.8	-7.9	-8.7
5	2.4%	2.8%	12.9%	6.4%	1.5%	10.6%	11.9	13.2	14.7	-7.2	-7.2	-8.6
Average ± STD	11.3% ± 6.2%	9.7% ± 9.1%	8.8% ± 4.7%	9.8% ± 2.0%	9.5% ± 7.6%	9.7% ± 4.8%	11.5 ± 0.7	12.9 ± 0.9	13.6 ± 0.9	-7.3 ± 0.8	-7.7 ± 0.4	-8.0 ± 0.5
Total average ± STD	9.9% ± 6.6%			9.7% ± 4.8%			12.7 ± 0.83			-7.7 ± 0.59		

In addition, the contributions of the proposed AAN EMG-based control strategy were compared to the contribution of the trajectory-tracking position control. For that, the EMG signals of the *tibialis anterior* and *gastrocnemius lateralis*, the motor torque, and the human ankle joint angle trajectories were analyzed considering the *unconditioned* and *conditioned* tasks. Table 6.9 presents the achieved results.

Table 6.9 – Variation of the EMG signals from *tibialis anterior* and *gastrocnemius lateralis*, and dorsiflexion and plantar flexion motor torques between *unconditioned* and *conditioned* tasks (a negative and a positive sign means a reduction and an increase, respectively, when comparing the variable measured at the *conditioned* task to the *unconditioned* task). Maximum dorsiflexion, and plantar flexion angles measured at the *conditioned* task

	Average $\pm$ STD	
	AAN	Position
EMG from <i>tibialis anterior</i>	-32.1% $\pm$ 23.2%	-29.2% $\pm$ 20.9%
EMG from <i>gastrocnemius lateralis</i>	-45.4% $\pm$ 21.0%	-42.8% $\pm$ 19.4%
Dorsiflexion Motor Torque	9.7% $\pm$ 6.4%	0.8% $\pm$ 2.6%
Plantar Flexion Motor Torque	9.7% $\pm$ 4.8%	-0.9% $\pm$ 4.1%
Maximum Dorsiflexion Angle (°)	12.7 $\pm$ 0.8	10.5 $\pm$ 0.1
Maximum Plantar Flexion Angle (°)	-7.7 $\pm$ 0.6	-5.8 $\pm$ 1.0

Table 6.9 shows that, **during *conditioned* tasks of both control strategies** (AAN EMG-based and trajectory-tracking position controls), **there was a reduction in the muscle activation of *tibialis anterior* and *gastrocnemius lateralis* muscles** compared to the *unconditioned* tasks. The decrease in activation of the *tibialis anterior* muscle during the AAN EMG-based control strategy (32.1% $\pm$ 23.2%) was similar to the decrease in activation of the same muscle during the application of the trajectory-tracking position control (29.2% $\pm$ 21.0%). An identical result was obtained for the decrease in activation of the *gastrocnemius lateralis* muscle, with decreases of 45.4% $\pm$ 21.0% and 42.8% $\pm$ 19.4% during the application of the AAN EMG-based and the trajectory-tracking position control strategy, respectively. **This means that the quasi-passive walking**

motion performed by participants at different gait speeds was similar between the two control strategies, as there was a similar reduction in muscle activation in both.

Nonetheless, despite a similar reduction in muscle activation, the ability of the AO to assist participants differed between the two control strategies. While during the AAN EMG-based control strategy the AO increased its dorsiflexion motor torque contribution ($9.7\% \pm 6.4\%$) to compensate for the lower activation of the dorsiflexor muscle (*tibialis anterior*), during the trajectory-tracking position control the increase in the orthosis contribution was very small ($0.8\% \pm 2.6\%$). The same behavior was observed for the plantar flexion motor torque contribution, in which (i) the AAN EMG-based control increased the motor torque of the AO ($9.7\% \pm 4.8\%$) to compensate for the lower activation of the plantar flexors (*gastrocnemius lateralis*); (ii) the trajectory control even decreased the motor torque of the AO ($-0.9\% \pm 4.1\%$) in the presence of lower plantar flexor muscle activity. This result is in line with what would be expected since trajectory-tracking position controls do not take into account the real-time muscular needs of the participant [27], [28]. Thus, these strategies typically do not adapt to the user's participation. Conversely, the proposed AAN EMG-based control strategy precepts the user's muscular participation and accordingly adapts the AO assistance. Thus, an increase in motor torque is expected as a result of a decrease in the EMG signals of the *tibialis anterior* and *gastrocnemius lateralis*.

As a result, **the ability to reach the maximum dorsiflexion angle (12.0°) was closer with the AAN EMG-based control ($12.7 \pm 0.8^\circ$) than with the trajectory-tracking position control ($10.5 \pm 0.1^\circ$).** This difference in joint angles was also seen in the plantar flexion angle, where **the AAN EMG-based control achieved a value ($-7.7 \pm 0.6^\circ$) closer to the maximum plantar flexion angle (-11.0°) than the trajectory-tracking position control ($-5.8 \pm 1.0^\circ$).** These results are also in line with what would be expected since the AAN EMG-based control not only invokes the user's participation but also attempts to correct the user's walking motion and provide assistance when and as much as needed.

In addition, when comparing the reference and measured ankle joint angles, the use of the AAN EMG-based control achieved an **average RMSE and delay of $4.94^\circ \pm 0.24^\circ$ and 182.0 ± 15.4 ms**, respectively. This is reflected in **a reduction in RMSE of $8.0\% \pm 4.2\%$ and a reduction in the delay of $20.7\% \pm 5.9\%$** compared to the trajectory-tracking position control.

At last, the replies of each participant to the applied questionnaire were analyzed. According to the provided replies (depicted in Figure 6.11), (i) 100% of the participants recognized that the **AAN EMG-based control provided more variable assistance**; (ii) 91.7% of the participants

recognized that the **AAN EMG-based Control provided more adequate assistance**; (iii) 91.7% of the participants felt that the **AAN EMG-based Control provided more assistance**; and (iv) 100% of the participants preferred the **AAN EMG-based Control for the prolonged use of the AO considering the existence of fatigue**. These results are promising in the sense that most of the participants who tested the proposed AAN EMG-based control strategy recognized its main advantages, i.e., the ability to provide assistance tailored to the user's needs at the time and in the amount required (when and as much as needed).

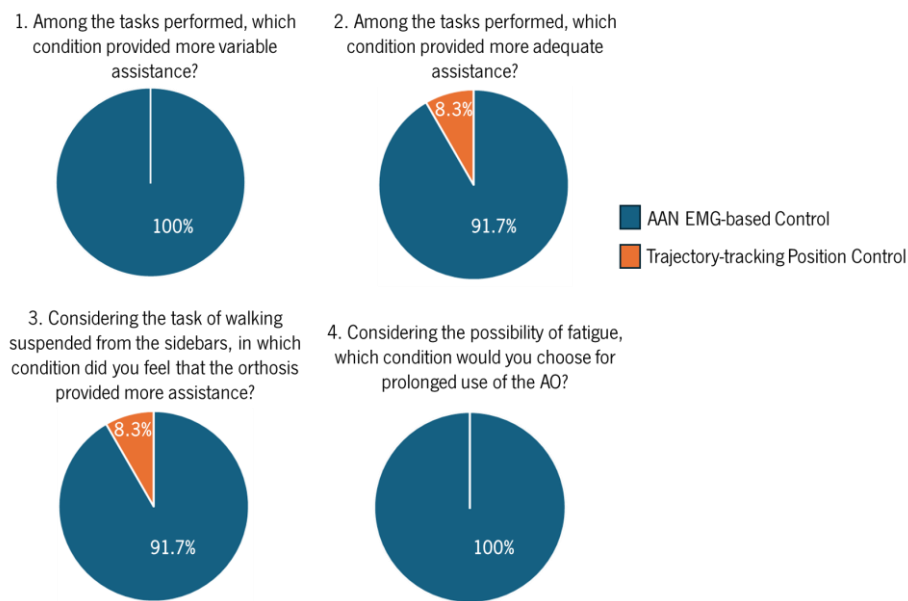


Figure 6.11 – Representation of the answers to the open questionnaire.

6.4 HUMAN-IN-THE-LOOP CONTROL

6.4.1 CRITICAL ANALYSIS OF RELATED WORK

In addition to changes in the physiological, kinematic, and spatiotemporal parameters **post-stroke patients typically start to face fatigue three months after stroke** [72], [160], [161]. Between 25% and 85% of post-stroke patients report fatigue, i.e., they have an increased need to rest or a lack of energy with high frequency (every day or nearly every day). **These fatigue episodes may influence the expected rehabilitation outcomes since they affect the patients' active participation during rehabilitation sessions.** Consequently, the ability to accomplish daily activities is compromised, negatively impacting patients' quality of life [160].

According to studies [37], [134], **patients' active participation should be encouraged** to achieve neuromuscular recovery during rehabilitation training. Thus, AAN HITL control strategies have been proposed for wearable assistive devices. With this control scheme, control parameters are adapted based on physiological signals obtained from the user [31], [162], [163]. **With the AAN HITL control strategy, it is expected that fatigue can be controlled while still allowing the patient to actively participate in the therapy.**

In AAN HITL control strategies, the physiological parameter commonly optimized is **energy expenditure**. However, the standard approach for estimating this signal relies on indirect calorimetry through a respirometer, which requires expensive and non-portable equipment, is time-consuming, produces noisy estimates, and is impractical for real-world applications [164]. At this level, different **AI algorithms have been employed to estimate energy expenditure** using data collected from wearable sensors (EMG, IMUs, and heart rate sensors) [52], [165]–[168]. However, to the author's best knowledge, only the study [168] has integrated the energy expenditure AI algorithm into a knee exoskeleton to perform a HITL control scheme.

In HITL control schemes, **the reduction of energy expenditure commonly occurs by adjusting the torque profiles of the wearable assistive device** [31], [50], [67], [168]–[170]. However, most of the available studies (i) depend on indirect calorimetry to estimate energy expenditure, which limits the wearability of the technology [31], [50], [170]; (ii) take too long to find the optimal control parameters, typically ranging from 24 to 72 minutes [31], [50], [67], [169]; and (iii) use wearable assistive devices with an electric cable-driven transmission [31], [50], [67], [169], [170]. The fact that wearable assistive devices use an electric cable-driven transmission means that an ankle torque pattern similar to the natural human torque profile can be used. However, according to Chapter 2, **electric motor-based controllers with a gear-based transmission** correspond to the most used actuators employed in wearable assistive devices for post-stroke rehabilitation. As already exposed for the knee joint in the study [168], for electric motor-based controllers with a gear-based transmission, the ankle torque pattern to be interpreted by the wearable assistive device must be different from the natural human torque pattern. Otherwise, the gait pattern will not be met because the instants of dorsiflexion and plantar flexion that should be performed will not be correctly executed by the wearable assistive device. Therefore, when designing a trajectory-tracking torque controller for an electric motor-based controller with a gear-based transmission, the torque profile to be used as the reference trajectory must be manually adapted to the intended application.

The AAN HITL control strategy proposed here is designed and integrated into the SmartOs system to address the limitations of existing strategies in the literature. The proposed control employs a regressor proposed in the study [168] to estimate energy expenditure based on data from four IMUs (eliminating the need for a respirometer). The innovation stems from (i) the development of a HITL control that allows the **ankle torque trajectory to be optimized according to the user's energy expenditure**; and (ii) the proposal and implementation of a torque control for an **electric motor-based controller with a gear-based transmission**.

6.4.2 METHODOLOGY

A. Hierarchical Control Architecture

The AAN HITL control proposed in this research follows a hierarchical architecture organized into high-, mid-, and low-levels, as depicted in Figure 6.12.

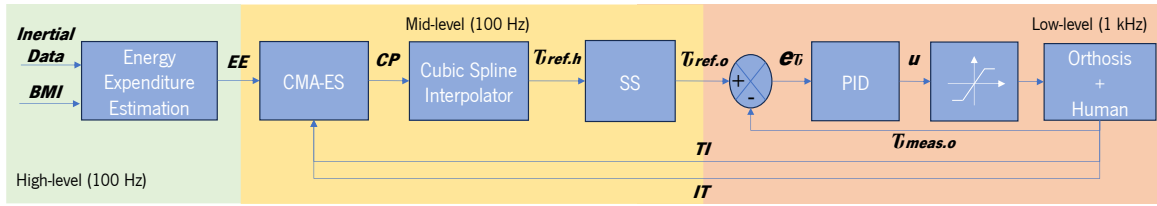


Figure 6.12 – AAN HITL control. *BMI*: body mass index defined through the mobile graphical application of the SmartOs system. *Inertial Data*: 3D acceleration data from the chest, right wrist, right waist, and left ankle recorded with the InertialLab system. *EE*: energy expenditure estimated every 10 seconds. *IT* and *TI*: cumulative interaction torque, and the integral of the reference ankle torque, respectively. *CP*: control parameters (magnitude of the plantar flexion and dorsiflexion torques at the push-off instant and mid-swing event, respectively). $T_{ref,h}$ and $T_{meas,o}$: human ankle joint reference torque and the measure SmartOs' motor torque, respectively. e_{Ti} : torque error. *u*: PID command. *SS*: speed scaling block (Equation 6.1). *PID*: Proportional-Integral-Derivative controller.

The high-level controller is responsible for (i) receiving and processing the 3D acceleration data from 4 IMUs (InertialLab system) positioned at the chest, right wrist, right waist, and left ankle, and the body mass index (*BMI*); and (ii) estimating the user's energy expenditure (*EE*) every 10 seconds. Details about data processing steps and energy expenditure estimation can be found in *B. Energy Expenditure Estimation*.

Once estimated, the energy expenditure value is sent to the mid-level, where it is used together with the cumulative interaction torque ($I\tau$) and the integral of the reference ankle torque ($T\tau$), as inputs to the HITL optimizer (*CMA-ES*). These two variables ($I\tau$ and $T\tau$) are computed for each gait cycle and are reset at the beginning of the gait cycle. The *CMA-ES* block presents a cost function (detailed in *D. CMA-ES optimizer*) that tends to be minimized through the variation of two control parameters (CP , representing the *CMA-ES* outputs), namely, the magnitude of the plantar flexion and dorsiflexion torques at the push-off instant and mid-swing event, respectively. These control parameters act as input in a cubic spline interpolator (detailed in *C. Ankle Torque Profile*), generating the human ankle joint reference torque ($\mathcal{T}_{ref,h}$). The $\mathcal{T}_{ref,h}$ is interpolated to the $\mathcal{T}_{ref,o}$ through the *Speed Scaling* (SS) block, according to Equation 6.1.

The $\mathcal{T}_{ref,o}$ is then sent to the low-level and it is compared with the SmartOs' motor torque ($\mathcal{T}_{meas,o}$), generating a torque error ($e\tau$). The $e\tau$ feeds the PID controller, using proportional, integral, and derivative gains of 300, 7.5, and 2.5, respectively. Considering the $e\tau$, the PID controller computes a PID command ($\mathcal{U}$) that is limited to maximum and minimum values of 2500 and -2500, through a saturator. This command is interpreted by the ankle orthosis, generating the corresponding motor torque.

With this control architecture, it is expected the **adaption of the control parameters to reduce the user's energy expenditure while still providing ankle support**.

B. Energy Expenditure Estimation

In this Ph.D. thesis, the energy expenditure was estimated in real-time using a machine learning regression model, namely an Exponential Gaussian Process Regression (EGPR), presented in the study [171]. This regression model was chosen since it outperformed other AI models, including boosted decision trees, bagged decision trees, support vector machines, and CNNs [171]. The EGPR model was trained and validated offline using data from a publicly available 10-participant dataset [172]. The training involved LOSOCV with a dataset including acceleration measurements from the chest, right wrist, left waist, and right ankle, as well as the participants' body mass index.

The trained regression model was implemented into the SmartOs high-level to estimate the energy expenditure in real-time, every 10 seconds. This time window was chosen to ensure that at least two respiratory cycles were captured, which is considered sufficient for accurate instantaneous metabolic cost estimation [171]. Moreover, despite training the EGPR with participants' body mass index and 3D acceleration data from the chest, right wrist, left waist, and right ankle, real-time tests

were conducted with the following data: participants' body mass index and acceleration data from the chest, right wrist, right waist, and left ankle. This alteration was done since (i) the SmartOs system does allow an IMU sensor to be positioned at the right ankle joint; and (ii) no differences were found in the energy expenditure estimation when using the IMU sensors at the right/left waist and ankle.

To estimate energy expenditure, the following data processing was applied. After receiving the 3D acceleration signals from the four specified body locations, these signals were filtered with a 4th-order Butterworth low-pass filter at 20 Hz. This frequency was chosen according to studies [165]–[167], since it provides a balance between signal attenuation and preservation of relevant information. Then, the filtered data were reorganized into 10-second windows, as suggested in the study [171]. At last, the mean absolute deviation was computed for each signal since it corresponds to a good feature to distinguish different physical activity intensities ([173]), being then normalized by the z-score method. Once processed, the data were interpreted by the EGPR, and the energy expenditure was estimated.

C. Ankle Torque Profile

The ankle torque profile represents the variation of the torque magnitude and sign in time, during a gait cycle. Figure 6.13 depicts the natural human ankle joint angle and torque, during level-ground walking at several gait speeds ranging from 1.0 to 4.0 km/h. Figure 6.13 shows that if the natural human ankle torque profile is used as a reference in a trajectory-tracking torque control applied to electric motor-based actuators with a gear-based transmission, the device will perform (i) small dorsiflexion immediately after the heel-strike event; (ii) a continuous plantar flexion until the end of the stance phase; and (iii) a torque around 0 N.m throughout the swing phase. In this way, the kinematic movement of the ankle joint would not be similar to the trajectory typically followed by this joint during the gait cycle. In addition, the area of the curve corresponding to the dorsiflexion motion must be identical to the area of the curve corresponding to the plantar flexion motion. Otherwise, the position of the ankle at the heel-strike event will be different for each gait cycle. It is therefore necessary to create a torque trajectory specific for electric motor-based actuators with a gear-based transmission.

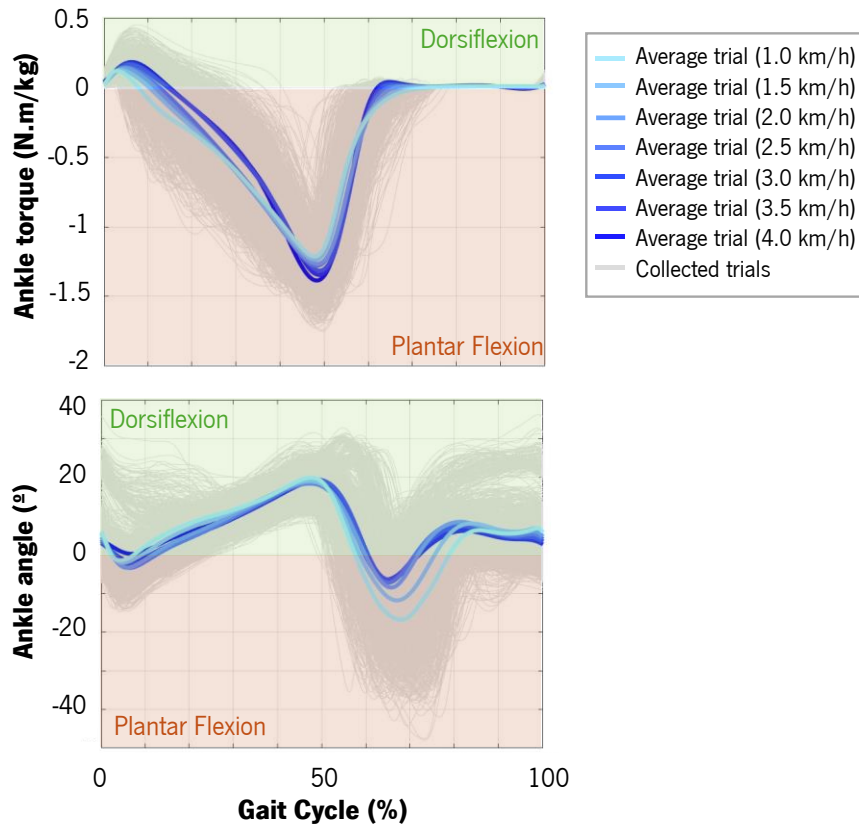


Figure 6.13 – Human ankle torque (top view) and ankle angle (bottom view). Adapted from the study [121].

In an attempt to find the best torque profile to use, an empirical test was performed with a healthy participant walking for one minute on a treadmill, assisted by the SmartOs system operating with trajectory-tracking position control, at a gait speed of 1.5 km/h. The average motor torque curve generated by the SmartOs system was then recorded for each gait cycle.

Figure 6.14 depicts the registered motor torque profile. According to Figure 6.14, the torque pattern was similar to the ankle angle pattern shown in Figure 6.13 (bottom view), as the dorsiflexion and plantar flexion phases coincided in time. On the other hand, the sum of the dorsiflexion and plantarflexion areas at the end of each gait cycle was approximately 0 N.m, indicating that the ankle position was approximately the same at the beginning of each gait cycle. Thus, the torque profile shown in Figure 6.14 seems to be a good candidate to be used as a reference in trajectory-tracking torque controls.

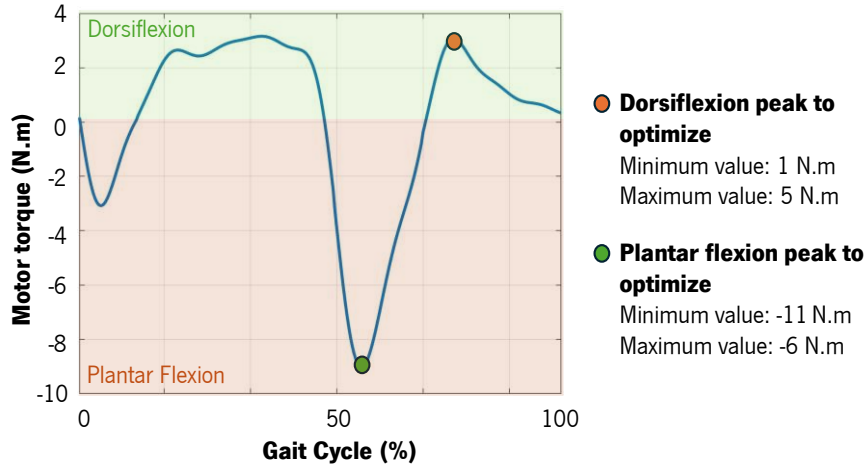


Figure 6.14 – SmartOs’ motor torque during walking with a trajectory-tracking position control.

As a low-level component of the HITL control, a trajectory-tracking torque control was developed. This trajectory-tracking torque control was designed to adjust the torque of the SmartOs’ actuator according to a reference torque profile. For that, a natural cubic spline interpolator algorithm was used to generate the reference torque profile (Figure 6.14) based on the optimized plantar flexion and dorsiflexion torque peaks during the swing phase determined by the CMA-ES algorithm (detailed in *D. CMA-ES optimizer*).

Initially, the points for defining the torque profile are identified (green and orange points depicted in Figure 6.14). The spline algorithm then constructs a piecewise polynomial cubic curve passing through these points by calculating three arrays of constants (a , b , and c), following the method described in [174]. By estimating the percentage of the gait cycle (P), the desired torque at each stage of the gait ($T(P)$) can be determined using Equation 6.2 [174]:

$$T(P) = t_i + a_i(P - p_i) + b_i(P - p_i)^2 + c_i(P - p_i)^3 \quad (6.2)$$

Where $i \in \{1, 2, \dots, n\}$, and $p_i \leq P < p_{i+1}$. Here, n represents the number of points defining the torque profile, and p and t are the arrays representing the coordinates of these points, specifically the percentage of the gait cycle and the corresponding torque value, respectively. In this thesis, the torque profile consisted of 20 points ($n = 20$), chosen to shape the curve appropriately.

D. CMA-ES optimizer

The HITL optimizer was designed to iteratively adjust two control parameters namely: the magnitude of the (i) plantar flexion torque at the push-off instant (between the terminal stance and the initial swing phases [green point in Figure 6.14]); and (ii) dorsiflexion torque at the mid- and

terminal swing phases (orange point in Figure 6.14). The magnitude of the plantar flexion torque at the push-off instant was optimized because it represents the moment in which it is required a propulsive force to move the body forward. As found in the study [175], this propulsive force at the push-off affects the energy expenditure of walking: the greater the force, the greater the energy. In addition, the plantar flexion torque at the push-off instant represents the control parameter that is typically addressed in the studies that developed AAN HITL control for the ankle joint [31], [48], [50], [67].

Furthermore, the magnitude of the dorsiflexion torque at the mid- and terminal swing phase was the second control parameter chosen to optimize, since post-stroke patients are characterized to present reduced dorsiflexion at this phase of the gait cycle, decreasing the foot's clearance from the floor, leading to toe dragging [71], [75].

The control parameters were adjusted to identify the optimal set that minimizes the user's physical effort. For this optimization problem, the user's physical effort was evaluated using a cost function (CF) calculated in real-time as a weighted sum of three parameters: the estimated energy expenditure (EE), the cumulative interaction torque (IT), and the integral of the reference ankle torque (TI), as shown in Equation 6.3. The weights assigned for each parameter (ω_1 , ω_2 , and ω_3) were the same as adopted in the study [168] and equal to 1.0, 1.0, and 0.5, respectively.

$$CF = \omega_1 EE + \omega_2 IT + \omega_3 TI \quad (6.3)$$

The interaction torque was chosen since it is directly related to the user's involvement and muscle effort. As reported in the study [168], a reduction in interaction torque corresponds to reduced muscle activity. The integral of the reference joint torque profile was also included in the calculation of the cost function to prevent the SmartOs system from promoting more dorsiflexion than plantar flexion and vice versa, which could result in unwanted assistance provided by the device.

In this optimization problem, a CMA-ES optimizer was implemented on the mid-level of the SmartOs system. The CMA-ES was already used in HITL controllers for lower limb exoskeletons [31], [50], [168]. It stochastically samples multiple candidates over multiple generations and adapts the covariance matrix of a multivariate normal distribution in real-time [176]. The initial parameters of the algorithm were set according to those reported in a previous study [168]. Only six initial parameters were adapted, namely: (i) the maximum and minimum plantar flexion torque, being defined as -6 and -11 N.m, respectively; (ii) the maximum and minimum dorsiflexion torque, being

defined as 5 and 1 N.m, respectively; and (iii) the initial plantar flexion and dorsiflexion torque values, being defined as -9 and 3 N.m, respectively.

As defined in the study [168], the CMA-ES optimization process was completed after 20 generations, each consisting of 6 iterations. After each iteration, the control parameters were automatically changed. Consequently, the optimization process took 20 minutes with each iteration taking 10 seconds to complete - the time needed by the EGPR model to estimate the energy expenditure. After the CMA-ES algorithm had completed the 20 generations, the optimal control parameters (magnitudes of the plantar flexion torque at the push-off instant and dorsiflexion torque at the mid-swing event) are found, i.e., the torque values that minimized the physical effort when using the SmartOs system.

E. Experimental Validation of AAN HITL Control

Three healthy participants (1 male and 2 females with an average age, body height, and body mass of 28.7 ± 2.5 , 165.3 ± 2.7 , and 66.3 ± 12.4 , respectively) without evidence of motor disorders participated in the study. Written informed consent was provided according to the University of Minho Ethics Committee (CEICVS 006/2020).

The protocol started by collecting the participant's gender, age, body height, and mass. Then, participants were equipped with 4 IMUs from the InertialLab system positioned in the chest, right wrist, right waist, and left ankle, to collect 3D acceleration data. Once instrumented with the sensor systems, participants were instrumented with the SmartOs system (Figure 6.15 – a)).

Then, all participants were instructed to perform walking tasks on a treadmill at a fixed gait speed (1.5 km/h), as depicted in Figure 6.15 – b). In the beginning, participants walked for 20 minutes with the proposed AAN HITL control strategy in order to perform the real-time optimization of the torque profile carried out by the CMA-ES optimizer. During this task, 120 iterations were conducted by the CMA-ES optimizer, generating new control parameters (magnitudes of the plantar flexion torque at the push-off instant and dorsiflexion torque at the mid-swing event) every 10 seconds. Once new control parameters were generated, new ankle torque profiles were defined as reference for the trajectory-tracking torque control. At each iteration, the CMA-ES optimizer analyzed the user's response [through the cost function (Equation 6.3)] and defined the next control parameters to be adapted. After 20 minutes, the optimal control parameters were found.

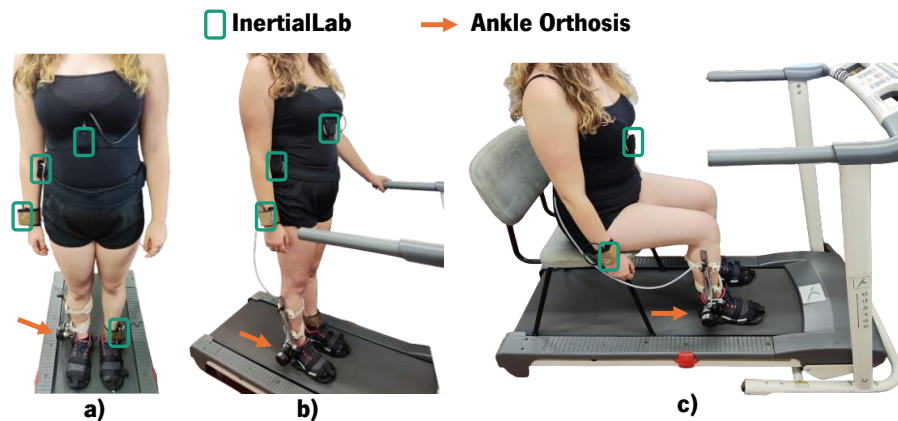


Figure 6.15 – a) Female participant equipped with the InertialLab and SmartOs systems; b) Position adopted to start the walking motion; and c) Rest position adopted.

After, all participants rested for 10 minutes in a sitting position, as illustrated in Figure 6.15 – c). After that, a 1-minute trial was conducted with the participants in a standing position, while the energy expenditure was estimated. This data collection was conducted to determine the basal energy expenditure between control strategies. Next, participants performed a 5-minute walking motion on a treadmill with three control strategies: zero-torque control, trajectory-tracking torque control with the non-optimal control parameters (plantar flexion and dorsiflexion torque values of -9 and 3 N.m, respectively), and trajectory-tracking torque control with the optimal control parameters. The order in which these tasks were performed was randomized across participants. Between each control strategy, participants rested for three minutes in a sitting position and performed the 1-minute trial for estimating the basal energy expenditure value. At last, participants performed a 5-minute walking trial on a treadmill without the AO, while the energy expenditure was estimated. This protocol is depicted in Figure 6.16.

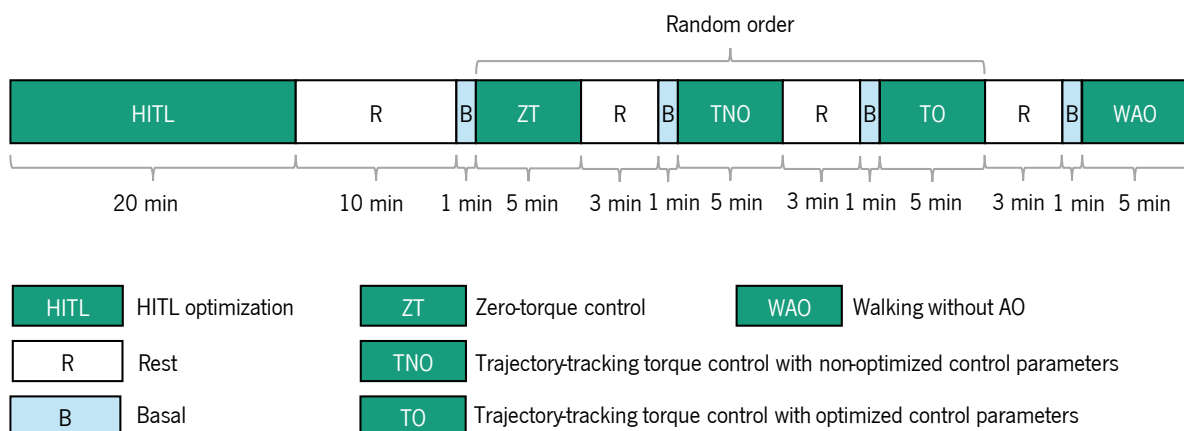


Figure 6.16 – Protocol designed to validate the proposed AAN HITL control strategy.

To evaluate the effectiveness of the HITL control strategy, the variation of the participant's physical effort and the two control parameters over the CMA-ES iterations were analyzed. For that, in order to assess the effect of walking with the device using optimized parameters, the user's energy expenditure was compared between the following conditions: walking with the SmartOs system operating under trajectory-tracking torque controls with optimized and non-optimized control parameters, walking without the AO, and basal condition. The analysis examined whether the implementation of the HITL control resulted in an increase or decrease in the user's physical effort. Boxplots were generated to illustrate the variation in the participant's energy expenditure across all tasks.

6.4.3 RESULTS AND DISCUSSION

Figure 6.17 illustrates the progress of the torque optimization using the CMA-ES algorithm, showing the variation of the peak dorsiflexion and plantar flexion torque values (the control parameters) and the evolution of the cost function value (the user's physical effort) over 120 iterations. From the results presented in Figure 6.17, it is verified that the values of the **control parameters (the plantar flexion and dorsiflexion torque peaks)** fluctuated significantly at the beginning of the optimization process, but **gradually converged to their optimal final values over time**. This result is in line with expectations as the CMA-ES optimizer refines its search and gets closer to the optimal solution with each iteration. Moreover, the value of the **objective function** (the user's physical effort) also fluctuated initially and then **steadily decreased as the CMA-ES algorithm learned and approached its minimum**. The algorithm took a total of 20 minutes to optimize the two control parameters of the AO, which is less than the 24 minutes taken by the fastest algorithm found in the literature to determine the optimal assistance [67].

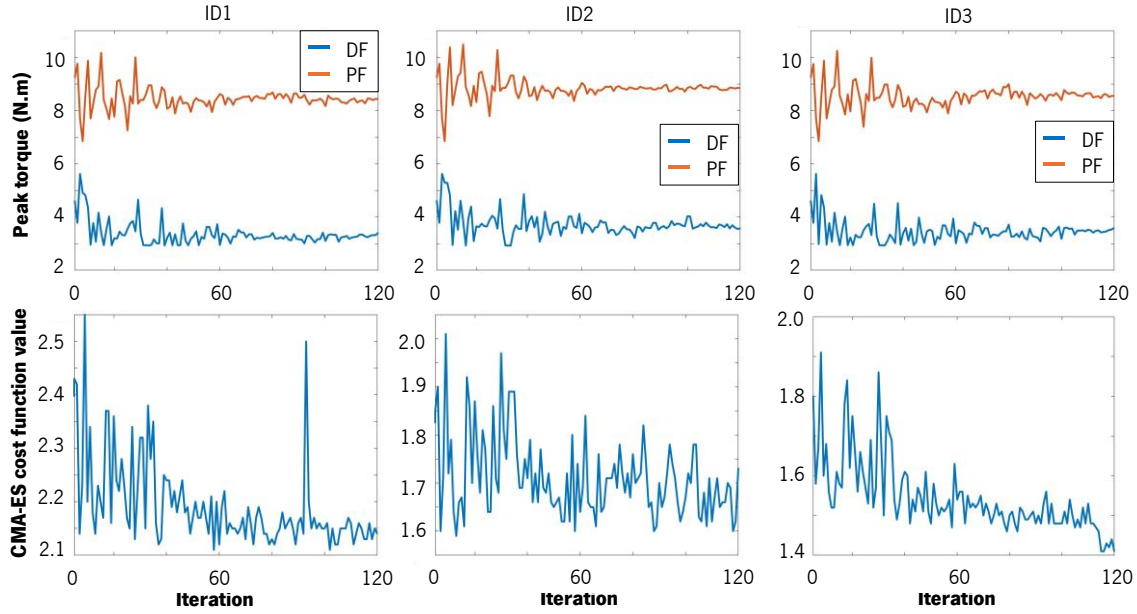


Figure 6.17 – Variation of the dorsiflexion (DF) and plantar flexion (PF) torque peaks (top view) and evolution of the cost function value (bottom view) during 120 iterations (20 minutes) of the CMA-ES optimizer for each participant. For ease of visualization, the plantarflexion torque values shown are the modulus of the real values.

Figure 6.18 shows the results of the effect on the energy expenditure after walking without the SmartOs system and walking with the SmartOs system operating under different control strategies. The basal energy expenditure estimate before each walking condition is also shown.

As can be seen in Figure 6.18, the basal energy expenditure value was similar throughout the data collection, which may indicate that the **participants had sufficient time to rest before performing a new 5-minute walking trial with and without the SmartOs system**. This result proves that all participants started the walking trials with and without the SmartOs system from the same state, i.e., from their basal energy expenditure value. Thus, any variation in energy expenditure was due to walking with and without the device using different control strategies and not due to participants not resting enough. Although previous studies have stated that participants rest for some time between different control strategies, this analysis was not conducted to infer whether the rest time was actually sufficient [31], [50], [67], [168]–[170].

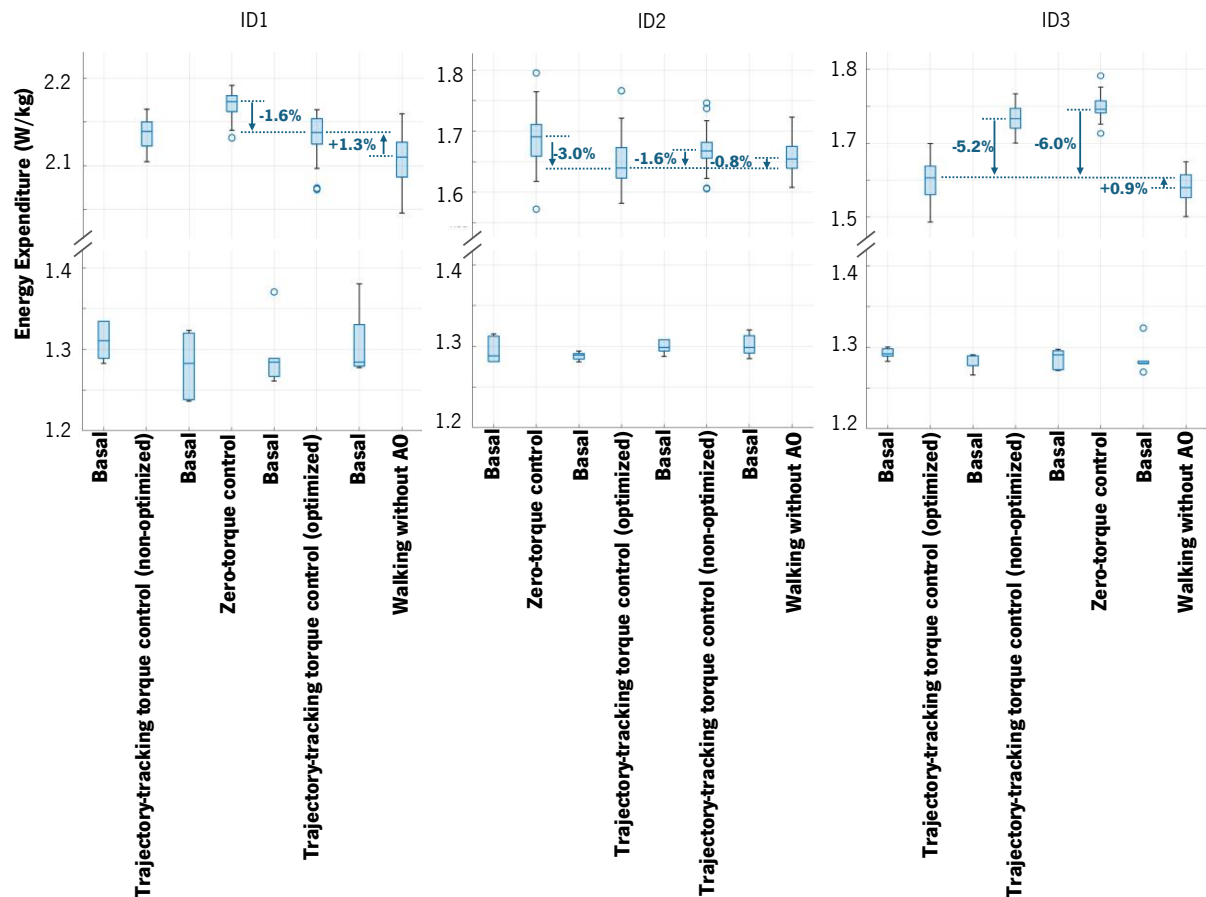


Figure 6.18 – Boxplots of the estimated energy expenditure per participant at different acquisition conditions.

Compared to the condition of walking with the SmartOs system operating under zero-torque control, the use of the trajectory-tracking control with optimized control parameters (optimized during the HITL trial) showed an average reduction of $3.53 \pm 1.84\%$, in the energy expenditure, with values ranging from 1.6% to 6.0% across all participants. Although promising, these results were inferior to those reported in previous studies, where reductions of between 7.3% and 24.2% were observed [31], [67], [168]–[170]. This phenomenon may be related to the fact that, in addition to the peak torque magnitudes, the studies also optimized the peak torque time, the torque rise time, and the torque fall time [31], [67], [169], [170]. Another aspect that may explain the difference between the reduction in energy expenditure reported in this Ph.D. thesis and the average values reported in other studies is the gait speed. According to the study [31], the reduction in energy expenditure varied with the gait speed, revealing reductions between 3% and 39% for gait speeds ranging from 2.7 km/h to 6.3 km/h, respectively. As the data collection performed in this thesis was carried out at a fixed gait

speed of 1.5 km/h, the results obtained were consistent with those reported by the study [31], at lower speeds.

Regarding the walking condition with the SmartOs system operating under trajectory-tracking control with non-optimized control parameters, the use of trajectory-tracking control with optimized parameters resulted in an average reduction of $2.27 \pm 2.17\%$ in energy expenditure. For the participant ID1, there was no difference in energy expenditure value between the two conditions. These results were lower than expected since the other studies reported reductions between 5.8% and 21.7% between trajectory-tracking torque controls with optimized and non-optimized control parameters [31], [168]–[170]. However, the small reduction in energy expenditure compared to the values found in the literature can be explained by the fact that the optimal control parameters found in this Ph.D. thesis during the HITL control strategy (-8.3 and 3.4 N.m for plantar flexion and dorsiflexion torque values, respectively) were closer to the values defined during the trajectory-tracking control strategy with non-optimized control parameters (-9.0 and 3.0 N.m for plantar flexion and dorsiflexion torque values, respectively).

At last, for the walking condition without the SmartOs system, the use of trajectory-tracking control with optimized parameters resulted in an average increase in energy expenditure of $0.47 \pm 0.91\%$, across the participants. Despite the average results, the energy expenditure of participant ID2 decreased by 0.80% for walking with the SmartOs system using trajectory-tracking control with optimized control parameters when compared to walking without a wearable assistive device. The average result is not aligned with those found in the literature, since previous studies have found that walking with the wearable assistive device operating under trajectory-tracking torque control with optimized control parameters resulted in a decrease in energy expenditure from 4.1% to 17.4% when compared to the condition of walking without the wearable assistive device [50], [168]–[170]. Although the results are different, they can be explained by the fact that an untethered device was used in the studies [169], [170], where the motor of the device was not supported by the user. This lack of weight may justify the difference in the variation of the energy expenditure obtained in the results of this Ph.D. thesis compared to those reported in the literature [169], [170]. Nonetheless, to better explain the difference between the results of this study and those found in the literature, it would be helpful to conduct more tests with a larger group of participants.

6.5 CONCLUSIONS

This thesis provides three contributions to the state of the art with the development,

implementation, and validation of three AAN control strategies, namely (i) **an LM-driven trajectory control capable of timely adapting the SmartOs assistance across six transitions** (St-LGW, LGW-St, LGW-SD, SD-LGW, LGW-SA, and SA-LGW); (ii) **EMG-based control with the ability to provide assistance when and as much as needed**, ensuring that the gait pattern is accomplished; and (iii) **HITL control capable of reducing the user's energy expenditure** by adjusting the control parameters while ensuring the gait.

These control strategies have been designed to target different therapeutic goals, making the SmartOs a versatile assistive system capable of adapting to the diverse and dynamic needs of different individuals, namely, post-stroke patients, as well as variations within the same individual.

Although the proposed AAN control strategies showed promising results, there are still opportunities for improvement. Specifically, there is a need to (i) conduct additional real-time validation procedures with more participants, including both able-bodied individuals and those with varying degrees of neurological impairments (addressed in Chapter 7); (ii) combine the developed AAN control strategies by empowering a wearable assistive device with the ability to simultaneously assist users when and as much as needed, according to their energy expenditure, and LM intentions.

7. SMARTOs CLINICAL VALIDATION

This chapter aims to evaluate the clinical evidence of SmartOs-driven personalized and repetitive assistance during locomotion training in post-stroke patients. It seeks to quantify the effects on biomechanical performance (including spatiotemporal parameters and range of motion of lower limb joints), functional performance (specifically muscular strength), and motor relearning during SmartOs-driven therapy.

The chapter starts with an introduction stating the main objectives to achieve with the SmartOs-driven gait training. It then describes the methodology developed to conduct the study, addressing the inclusion and exclusion criteria to select participants, the study design, the protocol, and the sensor-based and clinical outcome measures. The main effects achieved with the SmartOs-driven gait training are analyzed and discussed. The chapter ends with a comprehensive overview of the main conclusions regarding the effects of SmartOs-driven assistance during the locomotion of post-stroke patients.

7.1 INTRODUCTORY INSIGHT

Stroke remains a leading cause of long-term disability worldwide, often resulting in significant impairment of motor control and functional mobility. The use of robotic training has added a new dimension to post-stroke therapy, enabling more precise, adaptive, and patient-specific interventions [177]. Among these innovative tools is the SmartOs system, a novel rehabilitation device designed to improve motor control and functional mobility in post-stroke patients.

This thesis aims to evaluate the effectiveness of the SmartOs system in detail, **focusing on its impact on two post-stroke patients with different impairments.** Through a comprehensive assessment of **sensor-based and clinical outcome measures**, the study aims to provide insight into **how different control strategies can influence the recovery of post-stroke patients.**

By investigating the effects of SmartOs-driven therapy on the rehabilitation process of post-stroke patients, the study highlights the potential of personalized rehabilitation approaches. In the context of the available literature, this study defines specific outcome measures such as muscle activity, joint mobility, and gait symmetry, providing a nuanced understanding of how targeted interventions can promote biomechanical and functional improvements. The results of this study not only underline the impact of the SmartOs system but also contribute to the wider discourse on the future of post-stroke rehabilitation, highlighting the need for individualized therapeutic protocols adapted to the unique needs and conditions of each patient.

7.2 METHODOLOGY

7.2.1 PARTICIPANTS

The experimental protocol was carried out at the University of Minho in accordance with the ethical guidelines established by the Ethics Committee of the University of Minho (CEICVS 006/2020). Post-stroke patients were screened across the following inclusion criteria: (i) informed consent to participate in the study; (ii) hemiparesis at the right side due to either first ischemic or hemorrhagic stroke; (iii) age between 18 and 75 years; (iv) at least 6 months after stroke event; (v) body mass < 90 kg; (vi) FAC ≥ 3 ; (vii) MAS $\leq 1+$; (viii) ability to understand and follow the experimental instructions; and (ix) ability to walk on a treadmill. The exclusion criteria included those post-stroke patients who presented (i) bone fragility, orthopedic, cardiac, or respiratory disease that affects locomotion; (ii) wounds and/or cutaneous fragility in areas of contact with SmartOs; and (iii) aphasia, which may hinder effective communication/comprehension.

According to the inclusion and exclusion criteria, two post-stroke patients were selected, whose main characteristics are presented in Table 7.1.

Table 7.1 – Characteristics of the recruited post-stroke patients

Characteristic	Participant	
	ID1	ID2
Gender	Male	Female
Age	52	22
Body height (cm)	175	161
Body mass (kg)	80	51
Stroke etiology	Ischemic	Hemorrhagic
Time post-stroke (months)	15	7
FAC	4	4
MAS	1	1+
Ability to walk on a treadmill	✓	✓
Ankle deformity	Equinovarus foot	Equinus foot

7.2.2 PROTOCOL

Considering the experience of clinicians from 2CA – Braga and Braga Hospital, a clinical protocol was designed to study the effects of a SmartOs-driven therapy on post-stroke patients.

The study was organized in **19 sessions**, as depicted in Figure 7.1. At the baseline (session 1), all participants underwent a single session (**pre-training session/baseline assessment**) to record multimodal data, which was used to serve as a basis for the post-stroke patient assessment before the SmartOs-driven therapy. Then, post-stroke participants underwent a **familiarization session** with the SmartOs system (session 2). The intervention phase started at session 3 and it consisted of **15 training sessions** (2 sessions per week). During this phase, all participants also received conventional physiotherapy as per clinical practice. After the fifteen interventional sessions, post-stroke participants carried out a **post-training session** (session 18), by collecting multimodal data to infer the post-stroke participants' evolution upon SmartOs training. The **follow-up assessment** (session 19) took place one month after the intervention phase had been concluded.

Considering the state-of-the-art findings (Chapter 2), the clinical protocol outlined is in line with those reported in the available clinical trials that have used robotic training therapies (an average of fifteen sessions three times a week).

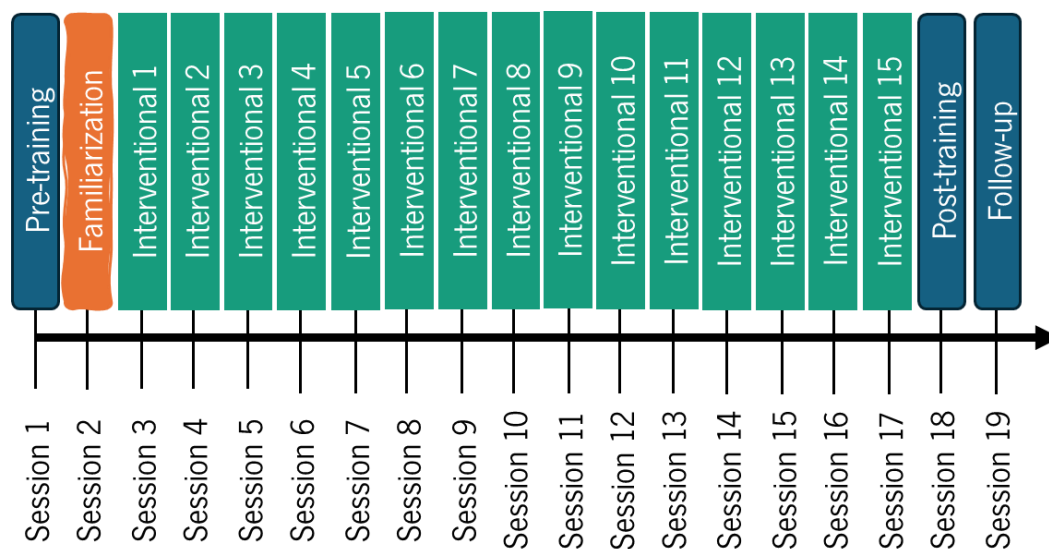


Figure 7.1 – Timeline of the SmartOs-driven training.

A. Pre-, post-training, and follow-up sessions

The pre-, post-training, and follow-up sessions performed at sessions 1, 18, and 19, respectively, consisted of an **assessment of the post-stroke patient status** including the steps detailed in Table 7.2. **The pre- and post-training sessions took around 60 minutes** and participants could rest as needed. **These sessions allow the analysis of the post-stroke patients' evolution**, in order to infer the main effects caused by the SmartOs-driven training at **physiological, kinematic, and spatiotemporal levels**. The **follow-up session** conducted one

month after the intervention phase was used to analyze the **retention effects**, i.e., whether the post-stroke patients have assimilated what they have learned during the SmartOs-driven training and have managed to retain it in the long-term.

Table 7.2 – Procedure adopted during pre-, post-training, and follow-up sessions

Procedure step	Duration (min)
Instrument participants with the 8-channel EMG Trigno Avanti, Xsens Awinda, and FootLab systems	10
Perform two MVCs per muscle	15
Perform Xsens Awinda system's calibration	
Carry out three repetitions of 10MWT	7
Carry out FAC	3
Carry out three repetitions of TUG	7
Carry out MAS	3
Carry out FMA-LE	10
Participant preparation for finishing session (sensors removal)	5

B. Familiarization session

The purpose of the familiarization session was to introduce the post-stroke patients to the SmartOs system, its functioning, sensors, and assistance modes (control strategies). More importantly, the steps shown in Table 7.3 were performed so that post-stroke patients could learn how to walk with the device.

Table 7.3 – Procedure adopted during the familiarization session with the SmartOs system

Procedure step	Purpose	Duration (min)
Warming exercises without the SmartOs system, including level-ground and treadmill walking at self-selected speed for 1 minute each	➤ To invoke muscle activation and flexibility; ➤ To appeal to mental preparation, focus, and concentration;	5
Instrument the participant with the SmartOs system	-	3

Dorsiflexion/plantar flexion movements in a sitting position. • Zero-torque control; • Trajectory-tracking position control using a ROM similar to the one measured during the MAS scale of the pre-training session;	Familiarization with the SmartOs system dynamics in passive and active control modes	5
Level-ground walking with the SmartOs system operating under zero-torque control for as long as it takes for the post-stroke patient to feel comfortable with the device (until a maximum of 10 minutes)*	Familiarization with the dynamics of the system in zero-torque mode during the walking motion and awareness of the additional mass imposed by the device	10
Level-ground anterior-posterior semi-step exercise performed by the paretic lower limb with the non-paretic upper limb supported on a chair	To improve motor relearning of the gait pattern during a static position. The therapist should assist the post-stroke patient in indicating the timing of push-off and heel-strike events	2
Level-ground walking with the SmartOs system operating under trajectory-tracking position control (1.0 km/h) for as long as it takes for the post-stroke patient to feel comfortable with the device (until a maximum of 10 minutes)*	To improve motor relearning of the gait pattern during the walking motion and synchronization with the SmartOs system. The therapist should assist the post-stroke patient in indicating the timing of push-off and heel-strike events	10
Treadmill walking at 1.0 km/h with the SmartOs system operating under zero-torque control for as long as it takes for the post-stroke patient to feel comfortable with the device (until a maximum of 10 minutes)**	Synchronization between walking with the SmartOs system in passive mode and the treadmill in motion	10
Treadmill walking at 1.0 km/h with the SmartOs system operating under trajectory-tracking position control (1.0 km/h) for as long as it takes for the post-stroke patient to feel comfortable with the device (until a maximum of 10 minutes)**	Synchronization between walking with the SmartOs system in active mode and the treadmill in motion. The therapist should assist the post-stroke patient in indicating the timing of push-off and heel-strike	10
Participant preparation for finishing session (sensors removal)	-	5

*The participant may use walking aids on the non-paretic limb or support provided by the therapist

** The participant may use the sidebar of the treadmill for support

C. Intervention sessions

The post-stroke patients underwent SmartOs-driven therapy over 15 training sessions, held twice a week. These sessions were divided into three different training protocols, each consisting of 5 sessions: **trajectory-tracking position control**, **adaptive impedance control**, and **AAN EMG-based control**, as shown in Figure 7.2.

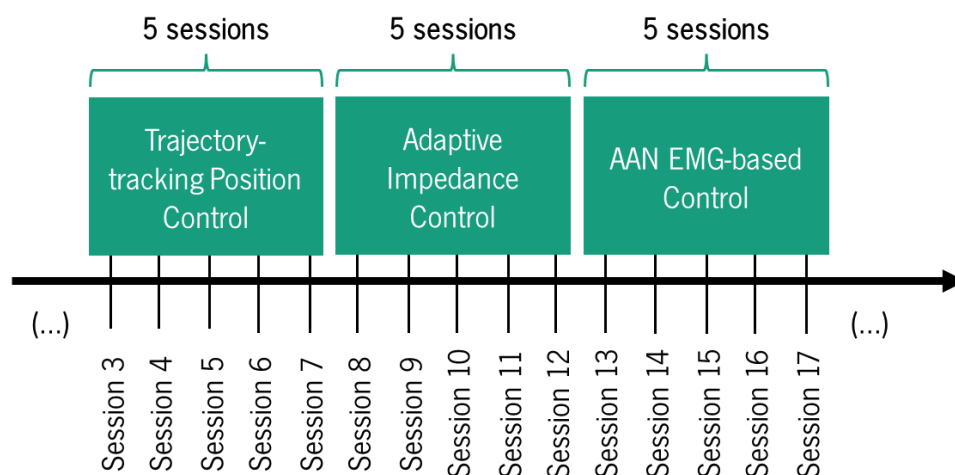


Figure 7.2 – Timeline of each assistive control strategy.

Both participants started with the trajectory-tracking position control, followed by the adaptive impedance and AAN EMG-based control strategies. By **starting with the trajectory-tracking position control**, the goal was that the post-stroke patient would initially be guided by the device in order to **remember and relearn a gait pattern close to the healthy one**. Although this control mode does not give the user freedom in the sense that it imposes a repetitive gait pattern, post-stroke patients were always asked not only to be guided by the device but also to actively try to perform the pattern that the device imposed on them.

After the first 5 sessions, post-stroke participants underwent another 5 sessions with the SmartOs system operating under an **adaptive impedance control**. During this training, the device's stiffness was decreased between a scale factor of 1 and 0.6 in specific phases of the gait cycle across the 5 sessions. **This was done to give more freedom to post-stroke patients to actively participate in the training therapy**. The phases in which the stiffness was decreased were chosen considering the performance of the post-stroke patient during the gait cycle. If the ankle joint movement at certain stages of the gait cycle was further away from what would be considered

a near-health movement, the stiffness was reduced by the therapist through the SmartOs' mobile graphical application, allowing the user to increase their interaction with the device. As a near-health movement of the ankle joint, the kinematic patterns performed by the post-stroke patient were compared to those available in the studies [121], [178].

Once the trajectory-tracking position and the adaptive impedance control strategies have been applied, post-stroke patients experienced the **AAN EMG-based control** for more five sessions. The therapist motivated the **post-stroke patients to engage in the therapy** by invoking their active participation, while the **AO corrected the post-stroke patients only when and as much as needed**.

In the first interventional session, the ankle joint ROM was initially set according to the ROM verified during the MAS scale of the baseline assessment, and it was progressively increased throughout the subsequent interventional sessions. In the same way, the walking speed was initially defined as 1.0 km/h at the first interventional session, and it was progressively increased according to the post-stroke patients' performance. Both ROM and walking speed were adapted using the SmartOs' mobile graphical application. Figure 7.3 shows the post-stroke patients walking with the SmartOs system during the intervention sessions.



Figure 7.3 – Post-stroke patients performing the interventional sessions.

Additionally, gait assessments were conducted at the beginning and end of each intervention session to evaluate the post-stroke patients' progress. For that, the post-stroke patients were asked to walk for one minute on both level-ground and treadmill, while physiological, kinematic, and spatiotemporal data were being collected.

At the end of each intervention session, the NASA Task Load Index questionnaire was applied to perform a workload assessment. Table 7.4 details all procedures followed during intervention sessions.

Table 7.4 – Procedure adopted during intervention sessions with the SmartOs system

Procedure step	Purpose	Duration (min)
Instrument participants with the 8-channel Trigno Avanti, and Xsens Awinda systems	To collect lower limb kinematic, physiologic, and spatiotemporal data during the interventional session	10
Perform two MVCs per muscle	To collect and analyze the evolution of maximum EMG signals per muscle	15
Perform Xsens Awinda system's calibration	-	
Level-ground walking for 1 minute, at a self-selected speed	To collect and analyze the evolution of lower limb kinematics, muscle activation, and spatiotemporal parameters during the walking motion: pre-session assessment	3
Treadmill walking for 1 minute, at 1.0 km/h		
Instrument the participant with the SmartOs system	-	4
Treadmill walking with the SmartOs system operating under zero-torque control and the treadmill switched off	To increase lower limb muscle recruitment and strength	5
Level-ground walking with the SmartOs system operating under zero-torque control with (i) therapist-induced balance disturbances at a self-selected speed (3 minutes); and (ii) a cadence imposed by a metronome (2 minutes)	With therapist-induced balance disturbances, the aim is to improve the post-stroke patient's balance and ability to react while trying to maintain their gait pattern. In metronomic cadence, the aim is for the post-stroke patient to improve the symmetry of their gait between the paretic and non-paretic leg	5
Level-ground walking with the SmartOs system operating under one of the three control strategies	Depending on the assistive control strategy to adopt, it is intended that	10
Treadmill walking with the SmartOs system operating under one of the three control strategies	post-stroke patients increase their lower limb joint ROM, gait speed,	5

Procedure step	Purpose	Duration (min)
	muscle strength, balance, human-robot interaction, and active participation level	
Level-ground walking for 1 minute, at a self-selected speed	To collect and analyze the evolution of lower limb kinematics, muscle activation, and spatiotemporal parameters during the walking motion. Post-session assessment	3
Treadmill walking for 1 minute, at 1.0 km/h		
Perform the NASA Task Load Index questionnaire	To conduct a subjective workload assessment	2
Participant preparation for finishing session (sensors removal)	-	5

7.2.3 DATA ACQUISITION

According to the state-of-the-art findings (Chapter 2), the main sensor-based outcome measures collected were (i) EMG signals from the right and left *tibialis anterior*, *gastrocnemius lateralis*, *biceps femoris*, and *rectus femoris* muscles to assess the physiological effects [16], [57], [58], [60], [81]; (ii) stance/swing ratio, gait speed, cadence, step length, and stride length to assess the spatiotemporal effects [16], [18], [58], [60], [81]; and (iii) lower limb joint angles in the sagittal plane to assess the kinematic effects [57], [60]. Besides, the FAC, TUG, and 10MWT scales were the clinical outcome measures most used to evaluate the effects of robot-driven training in the rehabilitation process of post-stroke patients [13], [15]–[17], [53]–[60], [80]–[83]. The post-stroke stage was assessed using the FMA-LE clinical scale [17], [53], [55], [58], [80]–[82].

This Ph.D. thesis considered these findings to design the evaluation methodology of the SmartOs clinical intervention. For that, the sensor-based outcome measures collected included: (i) physiological measures, analyzing the maximum EMG values from the right and left *tibialis anterior*, *gastrocnemius lateralis*, *biceps femoris*, and *rectus femoris* muscles achieved during the gait cycle; (ii) kinematic outcome measures, including an analysis of the maximum flexion and extension angles at the sagittal plane of the lower limb joints (right and left hips, knees, and ankles); and (iii) spatiotemporal parameters, namely, the step length, stride length, paretic/non-paretic stance, swing, and stance/swing ratio. For

that, post-stroke participants were instrumented with a surface 8-channel EMG system [Trigno Avanti (Delsys Incorporated, Natick, USA)] and an inertial system (Movella, Henderson, USA).

The EMG Trigno Avanti system was employed to acquire EMG signals from four lower limb muscles, namely, *tibialis anterior*, *gastrocnemius lateralis*, *biceps femoris*, and *rectus femoris* of both legs, as depicted in Figure 7.4. Before placing the EMG sensors, the skin above each muscle was gently cleaned with alcohol wipes to remove oils and dirt. After cleaning, the eight EMG sensors were attached to the skin using double-sided adhesive tape, following SENIAM recommendations. The system was configured to provide an envelope of EMG signals with a frequency of 148 Hz, by applying the RMS method.

Once instrumented with the EMG Trigno Avanti system, post-stroke patients were instrumented with the Xsens Awinda system to provide the lower limb joint angles at the sagittal plane, with a frequency of 100 Hz (Figure 7.4). Moreover, this system was also used to (i) segment the patient's left and right gait cycles according to the vertical position of the left and right foot, respectively; and (ii) compute the above-mentioned spatiotemporal parameters.



Figure 7.4 – Post-stroke patients instrumented with the Trigno Avanti and Xsens Awinda systems.

In addition, the clinical outcome measures employed were the TUG, 10MWT, FMA-LE, and MAS. To perform the TUG, post-stroke patients were asked to sit in a standard chair. The test started when they stood up from the chair, followed by walking a distance of 3 meters, turning 180°, walking back to the chair, and, finally, sitting down, as depicted in Figure 7.5. The time taken to complete the whole sequence was measured by the therapist using a chronometer, from the moment the patients started to stand up until they sat down again. This procedure was repeated three times [179].

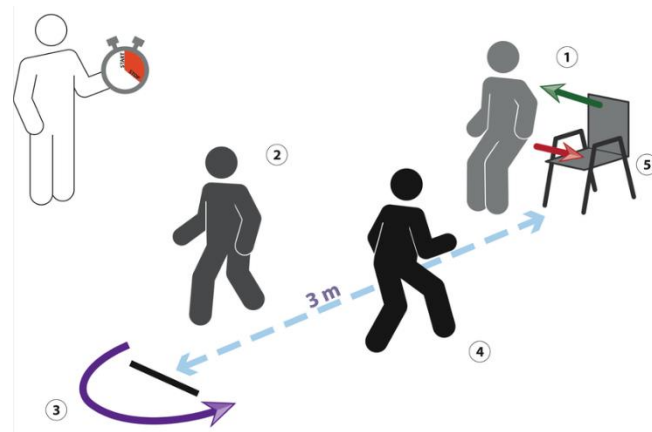


Figure 7.5 – TUG procedure. The post-stroke patient 1) stands up; 2) walks 3 meters; 3) turns 180°; 4) walks again 3 meters; and 5) sits down. Adapted from [180].

For 10MWT, a 10-meter straight path was marked on a level-ground floor, putting marks at 0, 2, 8, and 10 meters, as shown in Figure 7.6. Post-stroke patients were instructed to walk as quickly as possible without running and without performing uncomfortable patterns. At the same time, the therapist took the time by using a chronometer. The timer started when the patient's front foot crossed the 2-meter mark and stopped when the front foot crossed the 8-meter mark, recording the time taken to cover the central 6 meters without the patient's knowledge. This procedure was also repeated three times [181].

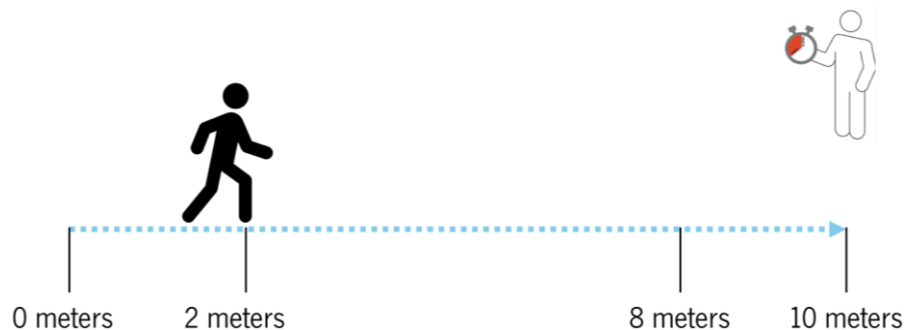


Figure 7.6 – 10MWT procedure.

Regarding the FMA-LE, this clinical scale is composed of a set of tasks that are scored on a scale from 0 to 2, with higher scores indicating better motor function. The maximum score to achieve is 28. In this research, four components of the FMA-LE were conducted, namely, (i) volitional movement within synergies (used to assess the maximal hip, knee, and ankle flexion and extension ability, and hip adduction in a supine position); (ii) volitional movement mixing synergies (used to assess the knee and ankle flexion ability in a sitting position); (iii) volitional movement with little or no synergy [used to assess the knee and ankle flexion ability in a standing position (the hip joint angle at the sagittal plane should be

close to 0°]; and (iv) coordination and speed (used to assess tremor, dysmetria, and time taken by each leg (paretic and non-paretic) to complete the task) [182].

The MAS quantifies spasticity into six levels based on the amount of resistance perceived by a therapist during the passive manual manipulation of the patient's ankle joint through its ROM, at a constant speed (Figure 7.7) [183]. In this Ph.D. thesis, the MAS was quantified for the *gastrocnemius* muscles.



Figure 7.7 – MAS procedure. Adapted from [184].

All sensor-based outcome measures were collected during (i) pre-, post-training, and follow-up sessions; and (ii) at the beginning and end of each interventional session. The clinical outcome measures were collected during pre-, post-training, and follow-up sessions.

Furthermore, participants' open comments were also annotated and the NASA Task Load Index questionnaire was applied at the end of each interventional session. This questionnaire corresponds to a multi-dimensional assessment tool that computes the overall workload score of a task or group of tasks across six factors, namely, mental demands, physical demands, temporal demands, own performance, effort, and frustration. Each factor is evaluated on a scale between 1 and 20 [185].

7.2.4 DATA PROCESSING

A. Sensor-based Outcomes

The acquired EMG signals from the *tibialis anterior*, *gastrocnemius lateralis*, *biceps femoris*, and *rectus femoris* muscles of both legs were interpolated to 100 Hz and segmented in gait cycles according to the vertical position of the left and right foot as measured by the Xsens Awinda system. After, the maximum value of each gait cycle for each muscle recorded during all sessions was determined. **The peak EMG value of *tibialis anterior* and *gastrocnemius lateralis* during**

the walking motion was defined as the primary physiological outcome measures in this research.

The lower limb joint angles of the right and left hips, knees, and ankles were also segmented in gait cycles. For all sessions, the following peak joint angles in the sagittal plane were then determined per gait cycle: (i) ankle dorsiflexion and plantar flexion angles in the swing phase; (ii) knee flexion angle in the swing phase; and (iii) hip flexion and extension angles. **The peak ankle dorsiflexion and plantar flexion angles in the swing phase were defined as the primary kinematic outcome measures in this research.**

Additionally, the spatiotemporal parameters (step length, stride length, stance time, swing time, and stance/swing ratio of both limbs, and paretic/non-paretic step and stride length ratio) were obtained from the Xsens Awinda system. For that, the vertical position of both left and right feet was employed to segment data into left/right steps/strides and stance/swing phases. Once segmented, the step/stride length for the left and right foot was accessed through the displacement of the IMU sensor position placed at the pelvis segment, considering the heel-strike and toe-off events. This procedure was followed since the IMU at the pelvis segment is close to the human center of mass; thus, it may be useful to infer the center of mass displacement during left/right steps/strides. **The gait speed and the paretic/non-paretic step and stride length ratio were defined as the primary spatiotemporal outcome measures in this research.**

Considering all of the above physiological, kinematic, and spatiotemporal values, boxplots were constructed for pre-training, trajectory-tracking position control, adaptive impedance control, AAN EMG-based control, post-training, and follow-up sessions. The variation of each sensor-based outcome measure was analyzed between (i) pre-training and post-training; (ii) post-training and follow-up; (iii) pre- and post-intervention for each control strategy.

B. Clinical Outcomes

The procedure followed to complete the TUG and 10MWT clinical scales was conducted three times. Then, the measured time of each clinical scale was averaged at the pre-, post-training, and follow-up sessions. Regarding the FMA-LE and MAS clinical scales, the obtained score was determined at the pre-, post-training, and follow-up sessions. The NASA Task Load Index was assessed at the post-intervention, averaging the obtained scores for each control strategy. **The TUG and 10MWT were defined as the primary clinical outcome measures in this research.**

7.3 RESULTS

The results of the two post-stroke patients are presented and analyzed separately because both presented different lower limb disabilities.

7.3.1 PARTICIPANT 1

Figure 7.8 depicts the boxplots of all sensor-based outcome measures at the pre-training and post-training of the trajectory-tracking position, adaptive impedance, and AAN EMG-based controls. Regarding the effects of the **trajectory-tracking position control strategy** for the **paretic limb** (right limb), **pre- and post-session assessments** revealed (i) a decrease in *biceps femoris* contraction (9.5 μ V), *gastrocnemius lateralis* contraction (4.0 μ V), knee flexion (1.1 $^{\circ}$), hip flexion (0.8 $^{\circ}$), step length (1.0 cm), and stance/swing ratio (1.2%); and (ii) **an increase in *tibialis anterior* contraction (7.6 μ V), ankle dorsiflexion (1.5 $^{\circ}$), and ankle plantar flexion (3.1 $^{\circ}$)**. The *rectus femoris* contraction, hip extension, stride length, stance time, and swing time did not show variations. **Pre- and post-session assessments** of the **trajectory-tracking position control strategy** for the **non-paretic limb** (left limb) showed (i) a decrease in *rectus femoris* contraction (1.1 μ V), *gastrocnemius lateralis* contraction (3.1 μ V), ankle dorsiflexion (1.3 $^{\circ}$), ankle plantar flexion (2.9 $^{\circ}$), stance time (2.9%), and stance/swing ratio (19.0%); and (ii) **an increase in hip flexion (1.4 $^{\circ}$), step length (1.2 cm), and swing time (2.9%)**. The *biceps femoris* contraction, *tibialis anterior* contraction, knee flexion, hip extension, and stride length did not show variations.

Advancing to the effects of the **adaptive impedance control strategy** for the **paretic limb**, **pre- and post-session assessments** revealed (i) a reduction in *gastrocnemius lateralis* contraction (3.4 μ V), and stance/swing ratio (3.5%); and (ii) **an increase in *tibialis anterior* contraction (12.2 μ V), ankle dorsiflexion (0.7 $^{\circ}$), step length (1.2 cm), and stride length (2.5 cm)**. The *biceps femoris* contraction, *rectus femoris* contraction, ankle plantar flexion, knee flexion, hip flexion, hip extension, stance time, and swing time did not show variations. For the **non-paretic limb**, **pre- and post-session assessments** exhibited (i) a decrease in *biceps femoris* contraction (1.1 μ V), *rectus femoris* contraction (1.8 μ V), *gastrocnemius lateralis* contraction (6.5 μ V), ankle dorsiflexion (0.9 $^{\circ}$), and hip extension (2.4 $^{\circ}$); and (ii) **an increase in ankle plantar flexion (0.9 $^{\circ}$), knee flexion (1.6 $^{\circ}$), hip flexion (1.0 $^{\circ}$), step length (2.2 cm), stride length (2.4 cm), and stance/swing time (4.6%)**.

Regarding the effects of the **AAN EMG-based control strategy for the paretic limb**, **pre- and post-assessments** revealed (i) a decrease in *biceps femoris* contraction (5.1 μ V), *gastrocnemius*

lateralis contraction (3.1 μV), ankle flexion (0.6 $^\circ$), hip extension (0.5 $^\circ$), stance/swing ratio (4.3%); and (ii) **an increase in *tibialis anterior* contraction (12.4 μV)**. The *rectus femoris* contraction, ankle plantar flexion, knee flexion, hip flexion, step length, stride length, stance time, and swing time did not show variations. **Pre- and post-assessments** for the **non-paretic limb** revealed (i) a decrease in *biceps femoris* contraction (8.1 μV), *gastrocnemius lateralis* contraction (8.0 μV), *tibialis anterior* contraction (10.1 μV), ankle dorsiflexion (1.4 $^\circ$), ankle plantar flexion (1.4 $^\circ$), hip flexion (0.5 $^\circ$), hip extension (2.6 $^\circ$), stance time (2.5%), and stances/swing ratio (6.3%); and (ii) **an increase in *rectus femoris* contraction (7.4 μV), step length (1.1 cm), and swing time (2.5%)**. The knee flexion and stride length did not reveal variations.

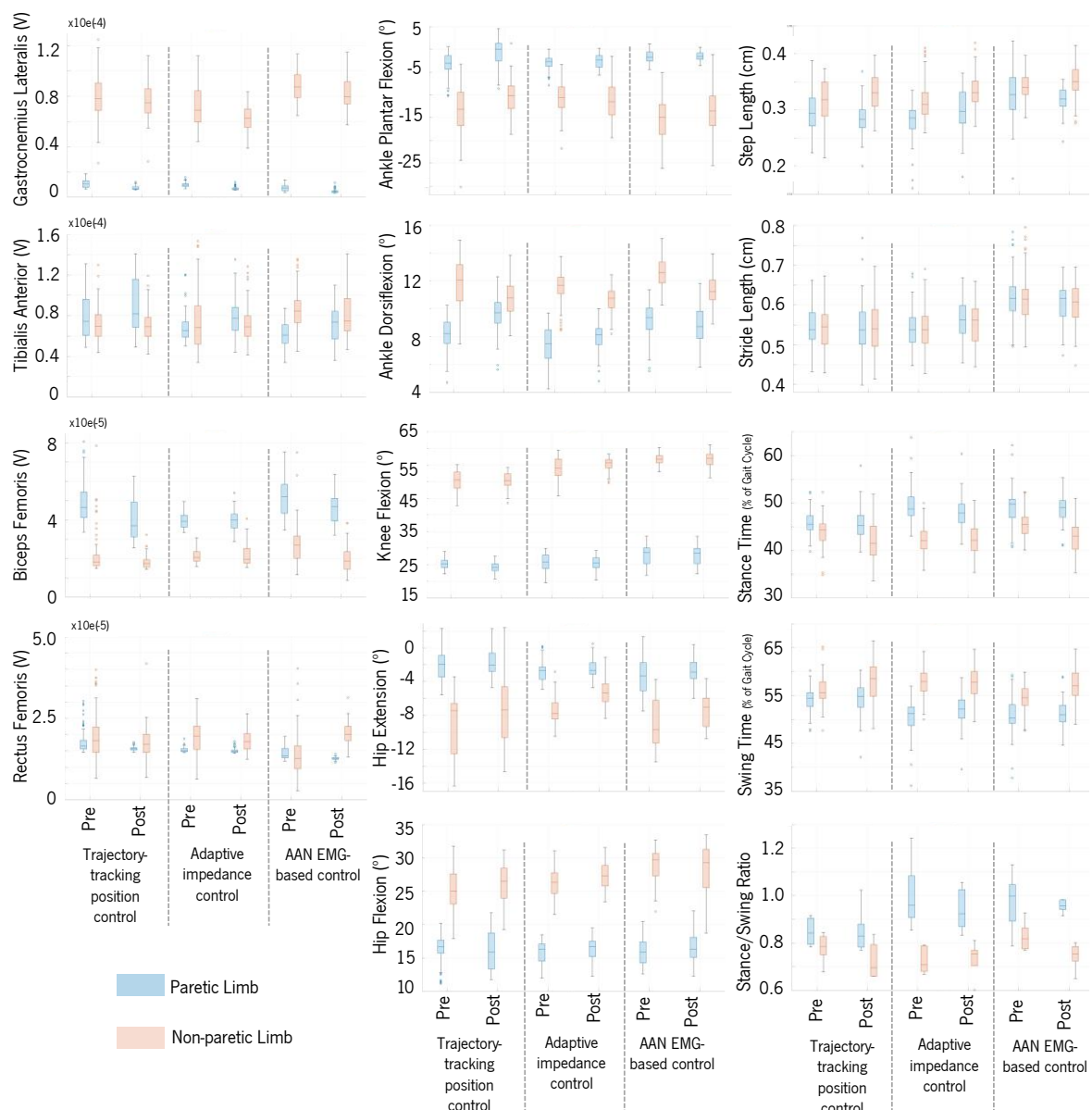


Figure 7.8 – Sensor-based outcome measures at the pre- and post-session assessment of trajectory-tracking, adaptive impedance, and AAN EMG-based controls.

Figure 7.9 shows the answers to the NASA Task Load Index questionnaire for each control strategy. According to the provided answers, the three control strategies (trajectory-tracking position, adaptive impedance, and AAN EMG-based controls) delivered **low feelings of insecurity, stress, and boredom**. Although low, the trajectory-tracking position control caused a higher frustration level (3.8) when compared to the remaining assistive control strategies, with the AAN EMG-based control being the strategy with the lowest frustration level (1.0). During the interventional sessions with the trajectory-tracking position control, the post-stroke patient reported pain in the ankle joint due to the physiognomy of the joint, which caused the AO to put pressure on the ankle. Regarding the temporal demand, the adaptive impedance, and AAN EMG-based controls revealed the lowest values (9.0 and 8.2, respectively), while the trajectory-tracking position control was classified with a score of 12.0. During the interventional sessions with this control strategy, the post-stroke patient reported that he felt his body stiffen because of the cold. With respect to the physical and mental demands, all control strategies revealed high levels. Nonetheless, the trajectory-tracking position control caused the highest mental demand (14.4), while the AAN EMG-based control demonstrated the highest physical demand (13.8). Despite being the most physically and mentally demanding, these control strategies were outperformed by adaptive impedance control in terms of overall effort (13.8). Moreover, even requiring a high level of effort, the feeling of success provided by adaptive impedance control (13.2) was greater than that provided by the other control strategies (11.0 and 10.8 for trajectory-tracking position and AAN EMG-based controls, respectively). **It is noteworthy that throughout the intervention therapies, the post-stroke patient felt motivated, stronger, faster, and more aware of his body.**

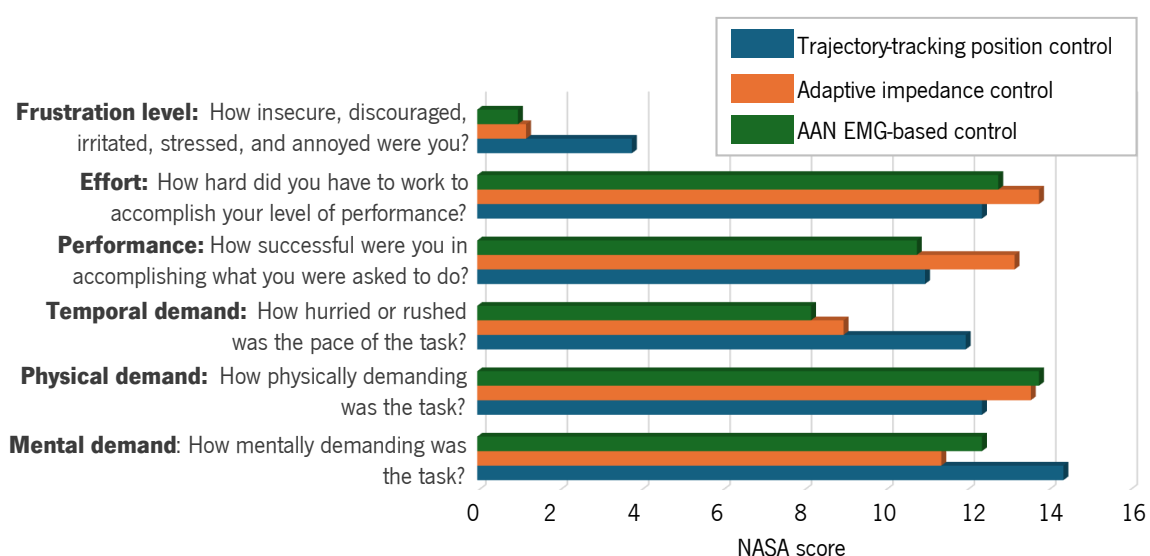


Figure 7.9 – Average NASA Task Load Index scores, considering the trajectory-tracking, adaptive impedance, and AAN EMG-based controls.

Figure 7.10 depicts the sensor-based outcome measures registered at the **pre-training, post-training, and follow-up sessions**. In general, for the **paretic limb**, the **pre- and post-training results** with the SmartOs system indicate that there was (i) a reduction in *gastrocnemius lateralis* contraction (2.9 μV), *tibialis anterior* contraction (15.9 μV), ankle plantar flexion (1.1°), and swing time (4.0%); and (ii) **an increase in *biceps femoris* contraction (12.6 μV), *rectus femoris* contraction (2.4 μV), knee flexion (7.4°), hip flexion (6.6°), step length (11.0 cm), stride length (18.9 cm), stance time (4.0%), and stance/swing ratio (13.0%)**. The ankle dorsiflexion and hip extension did not show variations. With respect to the **non-paretic limb**, the results indicated (i) a decrease in hip extension (2.2°), and swing time (2.3%); and (ii) **an increase in *biceps femoris* contraction (15.2 μV), *rectus femoris* contraction (14.8 μV), *gastrocnemius lateralis* contraction (7.5 μV), *tibialis anterior* contraction (17.3 μV), ankle dorsiflexion (1.2°), ankle plantar flexion (8.0°), knee flexion (10.4°), hip flexion (4.4°), step length (7.1 cm), stride length (22.4 cm), stance time (2.3%), and stance/swing ratio (7.2%)**. Furthermore, from the **pre- and post-training assessments**, the paretic/non-paretic (i) **step length ratio decreased by 2.7%, achieving a value of 1.00**; and (ii) **stride length ratio increased by 12.7%, achieving a value of 1.00**.

In addition, regarding the results of **assessing retention effects** on the paretic and non-paretic limbs, Figure 7.10 indicated (i) a reduction of *biceps femoris* contraction (5.3 μV), *rectus femoris* contraction (3.0 μV), *gastrocnemius lateralis* contraction (2.0 μV), *tibialis anterior* contraction (33.1 μV), ankle plantar flexion (0.8°), hip flexion (6.9°), step length (2.7 cm), and stride length (1.3 cm); and (ii) **an increase in ankle dorsiflexion (0.6°), knee flexion (0.9°), and hip extension (2.3°)**. The stance time, swing time, and stance/swing ratio remained preserved. Moreover, for the **non-paretic limb**, there was (i) a decrease in *rectus femoris* contraction (2.9 μV), ankle dorsiflexion (3.0°), knee flexion (3.3 degrees), hip flexion (0.7°), stride length (1.5 cm), and swing time (1.0%); and (ii) **an increase in *gastrocnemius lateralis* contraction (9.1 μV), *tibialis anterior* contraction (13.7 μV), ankle plantar flexion (8.4°), hip extension (6.7°), stance time (1.0%), and stance/swing ratio (2.6%)**. The *biceps femoris* contraction and step length remained preserved. Moreover, the the paretic/non-paretic (i) step length ratio remained preserved, maintaining a value of 1.00; and (ii) stride length ratio decreased by 7.6%, achieving a value of 0.93.

Figure 7.11 depicts the results obtained for the 10MWT, TUG, and FMA-LE clinical scales at the pre-, post-training, and follow-up sessions. Results from the **pre- and post-training assessments** revealed (i) **an average reduction of 8.2 seconds** and a standard deviation reduction of 1.9 s in the

10MWT; (ii) an **average reduction of 15.3 seconds** and a standard deviation reduction of 1.0 s in the **TUG**; and (iii) an **increase 2 levels** (from 13 to 15) in the score of the **FMA-LE**. Moreover, results from the **post-training and follow-up assessments** revealed (i) an average **decrease of 2.6 seconds** and no variation of the standard deviation in the **TUG**; (ii) an **increase of 3 levels** (from 15 to 18) in the score of the **FMA-LE**; and (iii) no variation in the average and standard deviation values of the 10MWT.

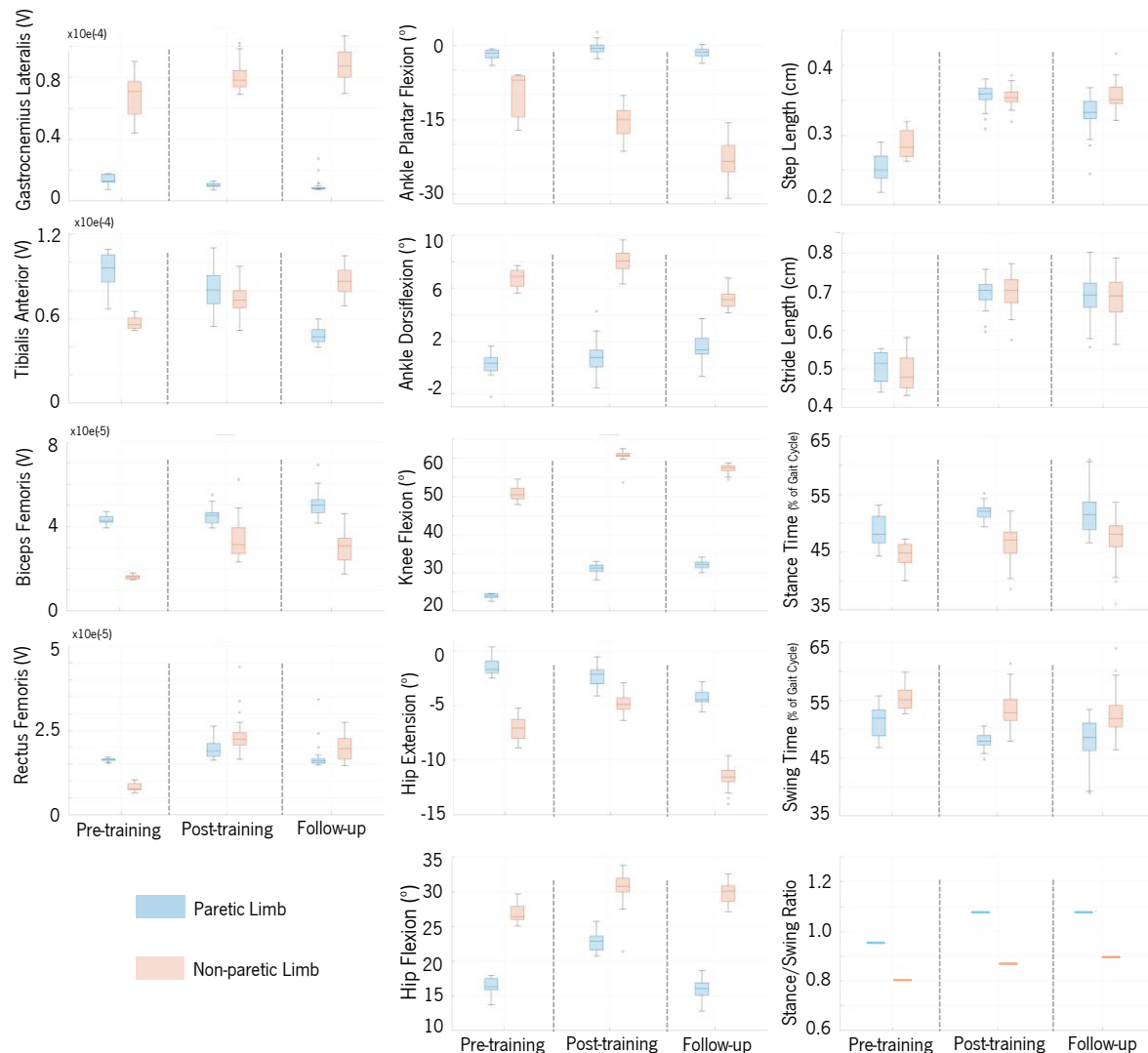


Figure 7.10 – Sensor-based outcome measures at the pre-training, post-training, and follow-up sessions.

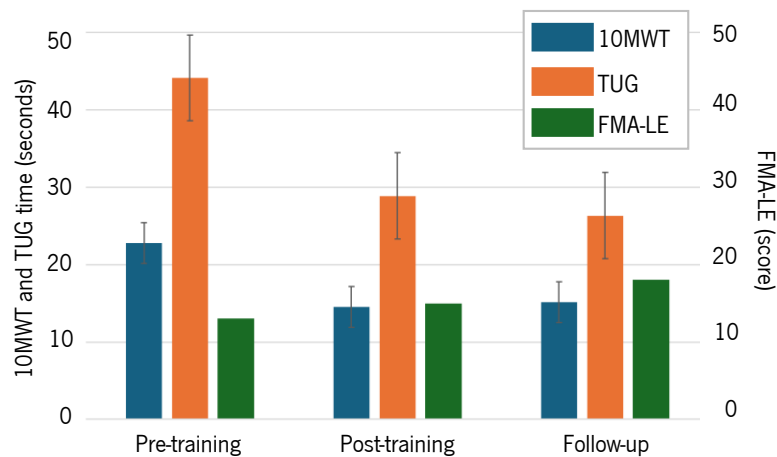


Figure 7.11 – Clinical outcome measures at the pre-training, post-training, and follow-up sessions.

7.3.2 PARTICIPANT 2

Figure 7.12 shows the boxplots of all sensor-based outcome measures for the trajectory-tracking position, adaptive impedance, and AAN EMG-based controls at both pre-training and post-training sessions. **Pre- and post-session assessments of the trajectory-tracking position control strategy for the paretic limb** (right limb) showed (i) a decrease in *biceps femoris* contraction (12.6 μ V), *rectus femoris* contraction (11.2 μ V), *gastrocnemius lateralis* contraction (4.9 μ V), *tibialis anterior* contraction (14.0 μ V), ankle dorsiflexion (4.2°), and stride length (3.3 cm); and (ii) **an increase in ankle plantar flexion (3.8°), knee flexion (1.0°), hip flexion (2.5°), hip extension (1.5°), step length (3.9 cm), and stance/swing ratio (2.6%)**. The stance time and swing time did not show relevant variations. For the **non-paretic limb**, the **pre- and post-assessments** of the trajectory-tracking position control revealed (i) a reduction in *biceps femoris* contraction (19.4 μ V), *gastrocnemius lateralis* contraction (16.2 μ V), *tibialis anterior* contraction (17.5 μ V), ankle dorsiflexion (2.4°), knee flexion (0.5°), hip extension (0.5°), stride length (3.1 cm), swing time (8.3%); and (ii) **an increase in ankle plantar flexion (2.7°), hip flexion (0.9°), step length (5.0 cm), stance time (8.3%), and stance/swing ratio (33.5%)**. The *rectus femoris* contraction did not show variations.

Regarding the **adaptive impedance control strategy for the paretic limb**, **pre- and post-assessments** indicated (i) a decrease in *biceps femoris* contraction (11.8 μ V), *rectus femoris* contraction (8.5 μ V), *gastrocnemius lateralis* contraction (5.2 μ V), *tibialis anterior* contraction (8.9 μ V), and ankle dorsiflexion (2.7°); and (ii) **an improvement in ankle plantar flexion (4.2°), knee flexion (0.5°), hip flexion (1.7°), hip extension (1.9°), step length (4.7 cm), stride length (3.8 cm), and stance/swing ratio (4.4%)**. The stance time and swing time did not present variations. For the **non-**

paretic limb, the **pre-** and **post-assessments** showed (i) a decrease in *biceps femoris* contraction (29.3 μ V), *rectus femoris* contraction (1.6 μ V), *gastrocnemius lateralis* contraction (15.2 μ V), *tibialis anterior* contraction (23.9 μ V), ankle dorsiflexion (1.0°), ankle plantar flexion (1.7°), and swing time (7.7%); and (ii) **an increase in hip flexion (2.4°), hip extension (1.3°), step length (7.2 cm), stride length (2.1 cm), stance time (7.7%), and stance/swing ratio (32.8%)**. The knee flexion did not show variations.

Pre- and post-assessments of the **AAN EMG-based control strategy** for the **paretic limb** indicated (i) a decrease in *biceps femoris* contraction (10.5 μ V), *rectus femoris* contraction (7.6 μ V), *gastrocnemius lateralis* contraction (6.6 μ V), *tibialis anterior* contraction (41.3 μ V), and ankle dorsiflexion (0.7°); and (ii) **an increase in hip extension (2.8°), step length (2.4 cm), stride length (2.7 cm), and stance/swing ratio (0.5%)**. The ankle plantar flexion, knee flexion, hip flexion, stance time, and swing time did not show relevant variations. For the **non-paretic limb**, **pre- and post-assessments** demonstrated (i) a reduction in *biceps femoris* contraction (18.7 μ V), *rectus femoris* contraction (2.6 μ V), *tibialis anterior* contraction (60.7 μ V); ankle plantar flexion (3.9°), and swing time (3.7 %); and (ii) **an increase in *gastrocnemius lateralis* contraction (13.1 μ V), knee flexion (0.7°), hip extension (1.0°), step length (5.3 cm), stride length (1.2 cm), stance time (3.7 cm), and stance/swing ratio (14.5%)**. The ankle dorsiflexion and hip flexion did not show variations.

Figure 7.13 shows the NASA Task Load Index scores obtained for each control strategy. According to the provided answers, the three control strategies (trajectory-tracking position, adaptive impedance, and AAN EMG-based controls) delivered **low feelings of insecurity, stress, and boredom** (below 2.8). The post-stroke patient always showed great motivation to use the device at each session. She also reported that she would like to have more intervention sessions. Regarding the temporal demand, the scores obtained for the trajectory-tracking position, adaptive impedance, and AAN EMG-based controls were close, being registered the values of 14.8, 13.0, and 12.0, respectively. With respect to the physical and mental demands, all control strategies revealed high levels, ranging from 13.8 to 15.8. Nonetheless, the trajectory-tracking position and the adaptive impedance controls caused the highest mental demand (15.8 and 15.6, respectively), while the trajectory-tracking position control demonstrated the highest physical demand (15.6). Moreover, this control strategy (trajectory-tracking position control) showed the highest score in terms of effort (17.2) and the lowest one regarding the feeling of success (15.0). On the other hand, the adaptive impedance and AAN EMG-based controls revealed the same score in terms of effort (15.2), but the feeling of success was higher for the adaptive impedance control (16.8). In addition, throughout the interventional sessions, the post-stroke patient

reported **more fluidity of movement** because she **felt that plantar flexion was more natural**. **She felt more symmetrical and more aware of her body, not only in the ankle joint but also in the knee and hip joints, and body posture.**

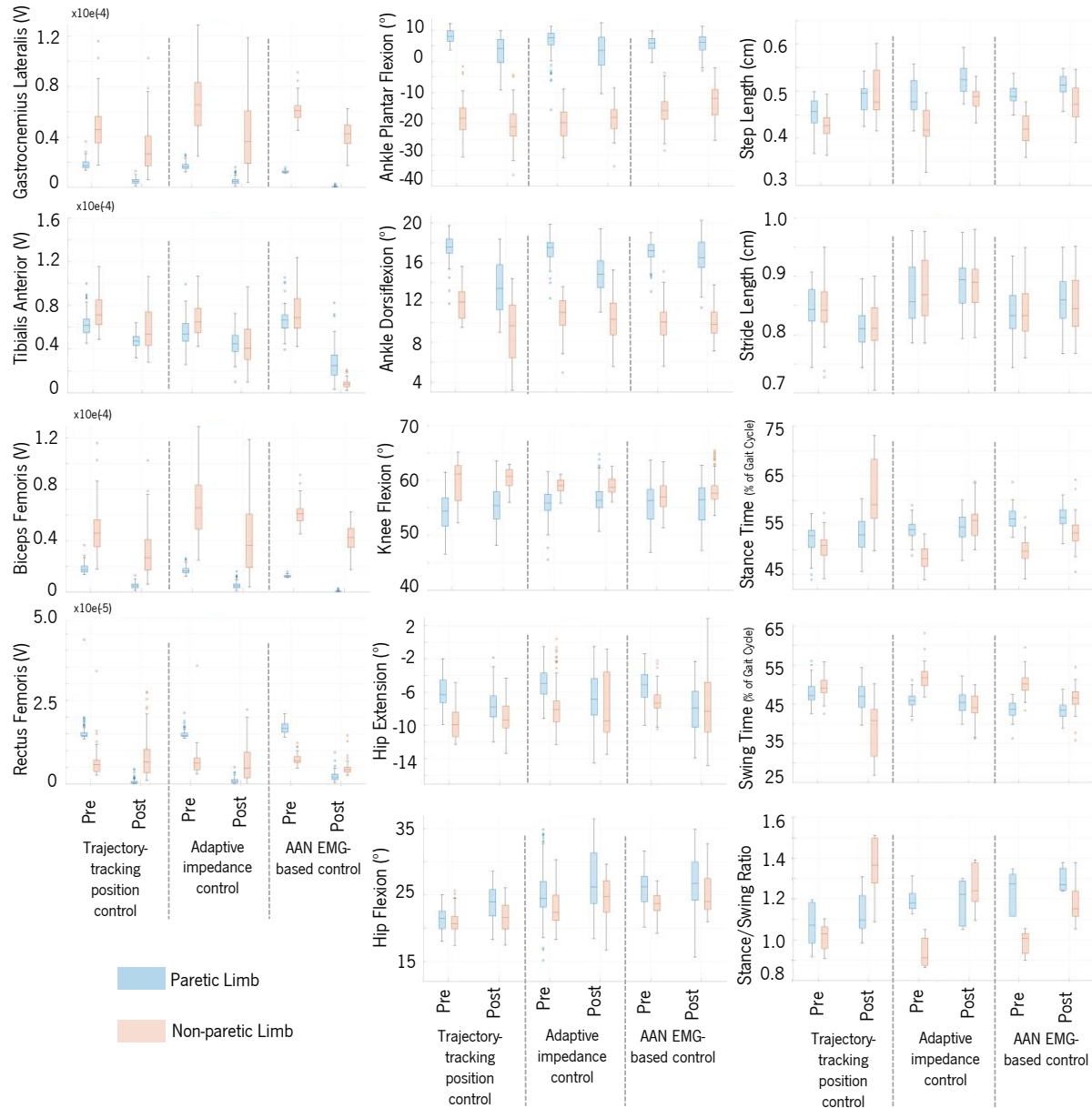


Figure 7.12 – Sensor-based outcome measures at the pre- and post-training of trajectory-tracking, adaptive impedance, and AAN EMG-based controls.

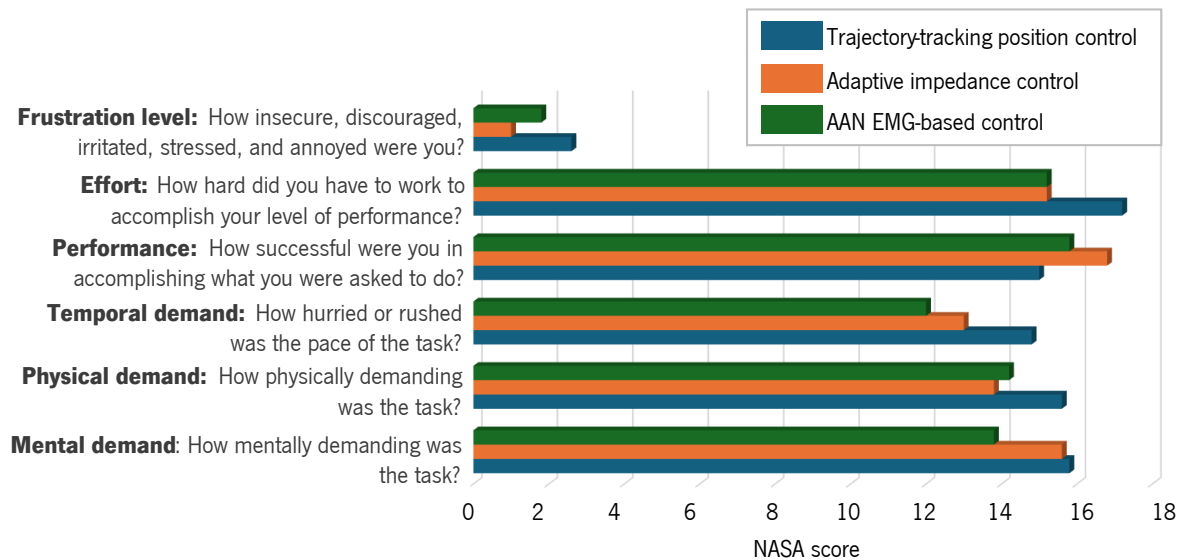


Figure 7.13 – Average NASA Task Load Index scores, considering the trajectory-tracking, adaptive impedance, and AAN EMG-based controls.

Figure 7.14 illustrates the sensor-based outcome measures recorded during the **pre-training, post-training, and follow-up sessions**. Overall, for the **paretic limb**, the **pre- and post-training results** with the SmartOs system indicate that there was (i) a reduction in *biceps femoris* contraction (1.9 μ V), ankle dorsiflexion (1.5°), hip flexion (5.4°), step length (4.3 cm), and swing time (1.2%); and (ii) **an improvement in *tibialis anterior* contraction (6.0 μ V), ankle plantar flexion (1.3°), hip extension (3.3°), stance time (1.2%), and stance/swing ratio (4.9%)**. The *rectus femoris* contraction, *gastrocnemius lateralis* contraction, knee flexion, and stride length did not show relevant variations. For the **non-paretic limb**, the results showed (i) a decrease in *biceps femoris* contraction (1.9 μ V), *tibialis anterior* contraction (1.4 μ V), ankle dorsiflexion (1.4°), ankle plantar flexion (0.8°), knee flexion (1.1°), hip flexion (1.7°), and swing time (2.4%); and (ii) **an increase in hip extension (4.4°), stance time (2.4%), and stance/swing ratio (10.6%)**. The *rectus femoris* contraction, *gastrocnemius lateralis* contraction, step length, and stride length did not reveal relevant variations. Moreover, from the **pre- and post-training assessments**, the paretic/non-paretic (i) **step length ratio decreased by 11.1%, achieving a value of 1.07**; and (ii) **stride length ratio decreased by 1.2%, achieving a value of 0.99**.

Additionally, Figure 7.14 shows the results of assessing retention effects on both the paretic and non-paretic limbs. For the **paretic limb**, results indicated (i) a reduction of ankle plantar flexion (2.1°), hip extension (2.9°), stance time (2.6%), and stance/swing ratio (10.4%); and (ii) **an increase in *tibialis anterior* contraction (1.3 μ V), ankle dorsiflexion (2.3°), knee flexion (1.9°), hip flexion**

(5.9°), step length (3.7 cm), and swing time (2.6%). The *biceps femoris* contraction, *rectus femoris* contraction, *gastrocnemius lateralis* contraction, and stride length remained preserved. For the **non-paretic limb**, results showed (i) a decrease in *gastrocnemius lateralis* contraction (5.8 μ V), *tibialis anterior* contraction (26.7 μ V), ankle dorsiflexion (0.6°), hip extension (2.2°), stance time (2.2%), and stance/swing ratio (7.5%); and (ii) **an increase in *biceps femoris* contraction (3.8 μ V), ankle plantar flexion (7.4°), knee flexion (1.3°), hip flexion (2.1°), step length (2.3 cm), stride length (1.5 cm), and swing time (2.2%).** The *rectus femoris* contraction remained preserved. Furthermore, the paretic/non-paretic (i) step length ratio increased by 0.7%, achieving a value of 1.08; and (ii) **stride length ratio increased by 0.7%, achieving a value of 1.00.**

Figure 7.15 illustrates the results for the 10MWT, TUG, and FMA-LE clinical scales at the pre-training, post-training, and follow-up sessions. The **pre- and post-training assessments** revealed: (i) an average increase of 0.2 seconds with a standard deviation decrease of 0.3 seconds in the 10MWT; (ii) an average **reduction of 0.3 seconds** with no change in the standard deviation in the **TUG**; and (iii) an **increase of 7 levels** (from 19 to 26) in the **FMA-LE score**. Additionally, the **post-training and follow-up assessments** revealed: (i) an average **reduction of 1.5 seconds** with no change in the standard deviation in the **10MWT**; (ii) an average **decrease of 2.9 seconds** with a standard deviation decrease of 0.5 seconds in the **TUG**; and (iii) no change in the score of the FMA-LE.

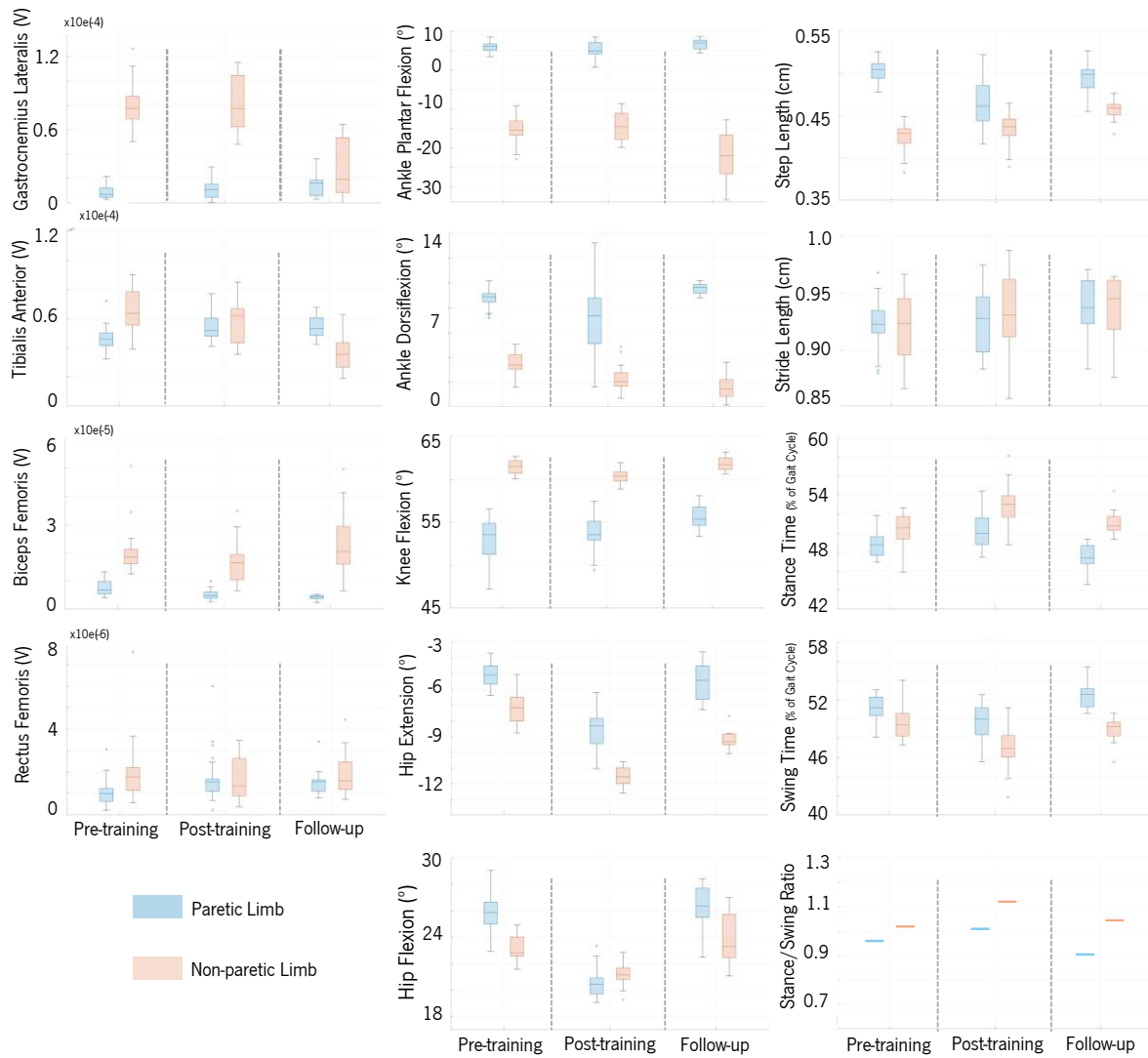


Figure 7.14 – Sensor-based outcome measures at the pre-training, post-training, and follow-up sessions.

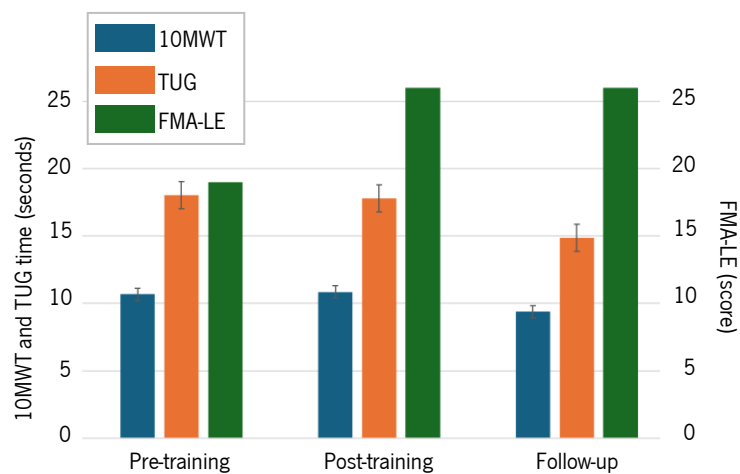


Figure 7.15 – Clinical outcome measures at the pre-training, post-training, and follow-up sessions.

7.4 DISCUSSION

This research presents **two case studies**, demonstrating the sensor-based and clinical outcomes of using the SmartOs system in rehabilitation sessions of two post-stroke patients. Sessions were conducted twice a week, for a total of fifteen training sessions. Each case study consisted of five consecutive sessions with the AO operating under trajectory-tracking position control, followed by five sessions with the AO operating under adaptive impedance control, and finally five sessions with the AO operating under an AAN EMG-based control approach. Pre- and post-session assessments were conducted during each training session, as well as two assessments before and after the fifteen training sessions, and a follow-up assessment one month after the final training session.

Since the two selected post-stroke patients presented different ankle impairments (as indicated in Table 7.1), the main effects of the SmartOs-driven therapy are discussed separately.

7.4.1 PARTICIPANT 1

With regard to the *tibialis anterior* muscle, all the control strategies promoted an increase in *tibialis anterior* contraction, with this increase being most evident after the application of the AAN EMG-based control strategy (12.4 μ V). This result is in line with what would be expected, as this control strategy is intended to elicit active participation from the user, which can increase muscle contraction. Despite assisting the hip and knee joints by using a therapist-led step-by-step exercise and a trajectory-tracking control based on lateral weight shift, similar results were found in the study [57], in which the *tibialis anterior* contraction was increased after performing walking training with the EksoNR. Additionally, post-stroke patient number 1 (ID1) presented an equinovarus deformity at the ankle joint, which is characterized by spasticity at the plantar flexors (*gastrocnemius*) and inverters (*tibialis posterior*) and a minimal contribution of the dorsiflexors (*tibialis anterior*) [69]. Considering this fact, the results obtained (i.e., an increase in *tibialis anterior* contraction) are promising, in the sense that the ***tibialis anterior* muscle was strengthened after the immediate application of AO**. However, despite being a promising result, the **increase in *tibialis anterior* muscle activity was not maintained at either the post-training or follow-up assessments**. This result is in line with those achieved in the study [16], in which the *tibialis anterior* muscle also reduced its activity after a training protocol with the EksoNR. Nonetheless, the authors pointed out that this result was obtained due to the fact that passive assistance was provided to the ankle joint, and active assistance was provided to the hip and knee joints [16]. In this Ph.D. thesis, the reduction of *tibialis anterior* contraction at the post-training and follow-up sessions may

indicate that more sessions may be needed to maintain high levels of *tibialis anterior* contraction in the long-term.

With respect to the *gastrocnemius lateralis* muscle, all control strategies caused a reduction in the *gastrocnemius lateralis* contraction, in which the trajectory-tracking position control provided the highest reduction (4.0 μV) and the AAN EMG-based control strategy provided the lowest reduction (3.1 μV). These results are not in accordance with those achieved in the study [57], in which it was concluded that after a training protocol with the EksoNR, the muscle activity of the *gastrocnemius medialis* was increased. Nonetheless, the study [57] did not characterize the post-stroke patients regarding their foot deformities. In this Ph.D. thesis, the ID1 presented an equinovarus foot, i.e., the *gastrocnemius* muscles were overactivated. The achieved results therefore suggest that **it was possible to reduce the overactivation of the *gastrocnemius lateralis* during the SmartOs-driven therapy**. In this context, these results are in line with what would be expected and are consistent with the purpose of administering botulinum toxin type A (BoNT-A), as an injection of BoNT-A promotes a reduction in muscle activity in the targeted muscle [69]. Moreover, post-training and follow-up assessments indicated that the *gastrocnemius lateralis* contraction was reduced compared to the pre-training; thus, as expected, the **SmartOs-driven therapy helped to reduce the *gastrocnemius lateralis* overactivity during gait in a post-stroke patient with an equinovarus foot**.

With respect to the kinematic performance, ankle dorsiflexion was (i) the most increased after the SmartOs-driven therapy with the trajectory-tracking control, followed by adaptive impedance controls; and (ii) decreased after the SmartOs-driven therapy with the AAN EMG-based control. Although *tibialis anterior* contraction was increased after SmartOs-driven therapy with AAN EMG-based control, the decrease in *gastrocnemius lateralis* contraction was the smallest with this control strategy. This may indicate that the *gastrocnemius lateralis* muscle could still be spastic and therefore limit dorsiflexion of the ankle joint. Furthermore, although the post-training results did not show any improvement in ankle dorsiflexion, the follow-up results suggest that ankle dorsiflexion capacity increased by 0.6°. These results suggest that the **SmartOs-driven therapy slightly increased ankle dorsiflexion**, namely for trajectory-tracking control and adaptive impedance controls. It is noteworthy that these findings are in line with what would be expected and are supported by the study [53], in which the use of the H2 exoskeleton operating with an impedance-based control promoted an increase in ankle dorsiflexion.

The trajectory-tracking position control was the only control strategy that increased the ankle plantar flexion, while the adaptive impedance and AAN EMG-based controls did not show any variations. Although trajectory-tracking position control was the control strategy that promoted the highest reduction in

gastrocnemius lateralis contraction, it was the strategy that promoted the highest increase in ankle plantar flexion. These results may be justified by the fact that trajectory-tracking position control promotes gait pattern training, thereby it may increase the ability to perform dorsiflexion and plantarflexion. Moreover, these results may indicate that the **spasticity may have been better controlled after SmartOs-guided therapy** with trajectory-tracking position control, **allowing an increase in ankle plantar flexion**, as expected. Despite promising results, it was supposed that at least the adaptive impedance control increased the ankle plantar flexion since a similar result was reported in the study [53]. Nonetheless, the increase in ankle plantar flexion was not sustained in either the post-training or follow-up assessments. This result suggests that while the immediate effects of SmartOs-driven therapy with the trajectory-tracking position control indicate an increase in ankle plantar flexion, additional sessions may be necessary to maintain these effects for the long term.

Concerning the spatiotemporal parameters, pre- and post-training assessments showed that the paretic/non-paretic (i) step length ratio varied from 0.87 to 1.00; and (ii) string length ratio varied from 1.02 to 1.00. Follow-up assessments indicated that the paretic/non-paretic stride length ratio remained consistent at 1.00, while the paretic/non-paretic step length ratio slightly decreased to 0.93. These findings suggest that the **SmartOs-driven therapy promoted a more symmetrical gait pattern**, as expected, as the step and stride lengths of the paretic and non-paretic limbs became more similar (i.e., closer to 1.00). These findings are also supported by the studies [16], [18], [58], [60], [81].

In addition, the pre- and post-training assessments of the 10MWT and TUG suggested that ID1 had become faster, i.e., his gait speed had increased, since the time taken to complete the 10MWT and TUG was reduced by an average of 8.2 seconds and 15.3 seconds, respectively. The standard deviation was also reduced, indicating that the post-stroke patient performed the 10MWT and TUG consistently and with less variation in gait speed. In addition, the results of the follow-up assessment showed no change in the 10MWT and a slight average reduction of 2.6 seconds in the performance of the TUG. Due to this reduction, the average time taken to complete the TUG at the follow-up assessment was less than that measured at the pre-training assessment. Therefore, the **SmartOs-driven therapy allows for an increase in gait speed and mobility**, as expected. These findings are also supported by the studies [13]–[18], [53]–[56], [58]–[60].

Despite actuating at the paretic ankle joint, the SmartOs-driven therapy revealed additional improvements. The pre- and post-training assessments indicated that the **knee flexion angles of the paretic limb increased by 7.4°**. This increase may be justified by the **increase in the biceps femoris muscle strength of the paretic limb (12.6 μ V)**. The studies [16], [58] confirmed this

assumption since the knee flexion angles of the paretic limb increased as a consequence of the *biceps femoris* muscle strengthening. Moreover, the study [57] also found that the *biceps femoris* contraction increased after gait training with EksoNR.

Moreover, **the stance time, step length, stride length, and stance/swing ratio of the paretic limb also increased, accompanied by a decrease in the swing phase.** These results are in line with what would be expected and are supported by the study [18].

Besides, the non-paretic limb also showed improvements, namely, an increase in *biceps femoris*, *rectus femoris*, *gastrocnemius lateralis*, and *tibialis anterior* contraction, ankle dorsiflexion, ankle plantar flexion, knee flexion, hip flexion, step and stride length, stance time, stance/swing ratio and a decrease in the swing time. These results are promising as they suggest **enhanced muscle function and gait efficiency**, with an **increased synergy between both paretic and non-paretic limbs**, indicating a more **stable and consistent walking performance**.

Improvements in FMA-LE were observed at both the post-training and follow-up assessments. In the post-training results, improvements in FMA-LE were primarily verified at the subscale procedure EII, specifically ankle dorsiflexion and knee flexion capacity. These findings are consistent with the already reported sensor-based kinematic results, which also showed improvements in ankle dorsiflexion and knee flexion at the post-training assessment. Further, at the follow-up assessment, improvements in the FMA-LE were noted in two subscale procedures: (i) EII, with improved ankle plantar flexion; and (ii) F, as both the paretic and non-paretic limbs completed tasks more quickly. Although no improvement in ankle plantar flexion during gait was observed at the follow-up assessment, this measure improved at the FMA-LE follow-up assessment. In addition, the improved times for both limbs in the FMA-LE coordination and speed tests can be justified by the improvements in the sensor-based physiological and kinematic outcome measures recorded in both limbs.

It is important to note that during the interventional therapies, the post-stroke patient reported **feeling increasingly motivated, stronger, faster, and more aware of his posture**, which is in line with the functional improvements discussed above.

7.4.2 PARTICIPANT 2

For the *tibialis anterior* and *gastrocnemius lateralis* muscles, all control strategies resulted in a reduction of their contraction ability, with the most considerable reduction observed after the implementation of the AAN EMG-based control strategy. This result may be related to the fatigue reported

by post-stroke patient number 2 (ID2) after each training session. These fatigue reports were more pronounced during training with the AAN EMG-based control, which may explain the greater reduction in *tibialis anterior* and *gastrocnemius lateralis* contractions. As the AAN EMG-based control strategy aims to invoke active user participation, it may lead to fatigue and, consequently, reduced *tibialis anterior* and *gastrocnemius lateralis* muscle activities. However, post-training and follow-up assessments showed (i) an increase in *tibialis anterior* contraction compared to pre-training levels; and (ii) no variations in *gastrocnemius lateralis* contraction compared to the pre-training assessments. Given that ID2 had an ankle *equinus* deformity characterized by plantar flexor spasticity and minimal dorsiflexor activity, the increase in *tibialis anterior* contraction indicates a positive rehabilitation outcome [69]. This result suggests that the **SmartOs-driven therapy contributed to the strengthening of the *tibialis anterior* muscle**. As far as *gastrocnemius lateralis* contraction is concerned, SmartOs-driven therapy did not seem to have any positive or negative long-term effects. However, the immediate reduction in *gastrocnemius lateralis* contraction after the application of the SmartOs system with the different control strategies may be related not only to the fatigue but also to an increase in the *gastrocnemius lateralis* spasticity control, since this muscle tends to be overactivated in patients with *equinus* foot [69]. Further studies, including more post-stroke patients with *equinus* deformity, are needed to make these results more robust.

Regarding the kinematic performance, ankle dorsiflexion was decreased after the SmartOs-driven therapy with all control strategies. This phenomenon may be related to the *tibialis anterior* muscle activity reduction registered. Despite this reduction, there was an increase in the ankle dorsiflexion angle at the follow-up assessment. This result is in line with what would be expected, as the activity of the *tibialis anterior* muscle also increased at the follow-up assessment, while there was no change in the activity of the *gastrocnemius lateralis* muscle. These results suggest that **SmartOs-driven therapy increased ankle dorsiflexion in the long term**, as expected. Notably, these results are consistent with the study [53] which found that the use of the H2 exoskeleton also promoted an increase in ankle dorsiflexion.

In addition, the ankle plantar flexion angle (i) increased after the SmartOs-driven therapy with the trajectory-tracking position control and adaptive impedance controls; and (ii) did not vary after the SmartOs-driven therapy with the AAN EMG-based control. Although the *gastrocnemius lateralis* decreased its activity after SmartOs-driven therapy with the trajectory-tracking position and adaptive impedance controls, the ankle plantar flexion angle increased. This result may indicate that the **spasticity of the *gastrocnemius lateralis* was controlled, allowing the plantar flexion angle to increase during the walking motion**. The same assumption cannot be made for the SmartOs-driven therapy

with the AAN EMG-based control. Although *gastrocnemius lateralis* muscle activity also decreased, which may indicate overactivation reduction, the ankle plantar flexion angle did not change. This phenomenon may be related to the fatigue reported by ID2 after the SmartOs-driven therapy with the AAN EMG-based control. Moreover, post-training assessments revealed that the ankle plantar flexion angle was increased compared to the pre-training levels. This finding suggested that the **SmartOs-driven therapy contributed to an increase in plantar flexion angle**, which is in line with the conclusions reported in the study [53]. However, the achieved ankle plantar flexion angles were not maintained at the follow-up assessments, which may indicate that **more therapy sessions should be performed to guarantee the long-term effects of receiving the SmartOs-driven therapy**.

In terms of spatiotemporal parameters, pre- and post-training assessments showed that the paretic/non-paretic (i) step length ratio decreased from 1.18 to 1.07; and (ii) stride length ratio slightly decreased from 1.00 to 0.99. Follow-up assessments showed a slight increase in the paretic/non-paretic step length ratio to 1.08 and the stride length ratio to 1.00. These results suggest that the **SmartOs-driven therapy promoted a more symmetrical gait pattern**, as the step and stride lengths of the paretic and non-paretic limbs became more similar, approaching a perfect ratio of 1.00. These findings are also supported by the studies [16], [18], [58], [60], [81].

Additionally, the pre- and post-training assessments of the 10MWT and TUG indicated that ID2 **maintained her average gait speed and mobility** as the time taken to complete both tests remained similar. However, the standard deviation of the 10MWT decreased in the post-training assessment, suggesting that **the post-stroke patient performed the 10MWT with a more consistent gait speed**. Furthermore, the results of the follow-up assessment showed that ID2 **became faster and with more mobility**, with reduced times to complete both the 10MWT and TUG, and a reduced standard deviation during the TUG. Therefore, the **SmartOs-driven therapy contributed to an increase in gait speed**. These results are supported by other studies [13]–[18], [53]–[56], [58]–[60].

Despite targeting the paretic ankle, the SmartOs-driven therapy resulted in additional improvements. Pre- and post-training assessments showed increases in hip extension, stance time, and stance/swing ratio in both the paretic and non-paretic limbs, and a decrease in swing time in the non-paretic limb. These results are promising, suggesting **improved synergy between the paretic and non-paretic limbs**, indicating **more stable and consistent gait performance**.

Additionally, **improvements in FMA-LE were observed at the post-training assessments and maintained at the follow-up assessments**. In the post-training results, improvements in FMA-LE were verified at the subscale procedure EIII, EIV, and F, corresponding to ankle dorsiflexion, knee

flexion, and coordination and speed abilities, respectively. These findings are consistent with the already reported sensor-based kinematic results, which also showed improvements in ankle dorsiflexion during the gait at the post-training assessment. Although no improvement in knee flexion during gait was observed at the post-training assessment, this measure improved at the FMA-LE post-training. Further, dysmetria and tremors were no longer verified.

The post-stroke patient consistently demonstrated a **high level of motivation to engage with the SmartOs system** during each session and expressed a **desire to increase the number of intervention sessions**. In addition, she reported a progressive **improvement in movement fluidity** over the sessions, highlighting in particular that **plantar flexion felt more natural**. The patient also noted an **improved sense of symmetry** and **increased body awareness**, not only in the ankle but also in the knee, hip joints, and **overall body posture**. These personal perceptions are extremely important and confirm the functional improvements seen with sensor-based and clinical outcome measures.

7.5 CONCLUSIONS

The aim of this study was to evaluate the effectiveness of the SmartOs system, a novel rehabilitation tool, in improving motor control and functional mobility in post-stroke patients. Through two detailed case studies, the sensor-based and clinical outcome measures were examined using different control strategies – trajectory-tracking position, adaptive impedance, and AAN EMG-based controls - over fifteen training sessions.

Due to the different conditions of both post-stroke patients, the effects of the SmartOs-driven therapy were assessed separately. For the first post-stroke patient (ID1), **presenting equinovarus deformity**, all control strategies contributed to (i) an **increase in *tibialis anterior* muscle contraction**, particularly with the AAN EMG-based control strategy, which aligns with the goal of encouraging active muscle engagement; and (ii) a **reduction in *gastrocnemius lateralis* contraction**, particularly with trajectory-tracking position control, which **suggests a decrease in muscle spasticity**. Moreover, **ankle dorsiflexion was improved** with trajectory-tracking and adaptive impedance controls and **ankle plantar flexion increased** only with trajectory-tracking position control. **A more symmetrical gait pattern was verified**, with **step and stride lengths becoming more balanced between the paretic and non-paretic limbs**, combined with **improvements in gait**

speed. Despite the positive outcomes, **retention assessments highlighted the necessity for continuous therapy** to maintain gains in muscle activity and functional mobility.

In the second post-stroke patient (ID2), who presented with an **equinus deformity**, the retention assessments highlighted the **strengthening of the *tibialis anterior* muscle** and the **increase in ankle dorsiflexion**. Moreover, immediate **improvements in ankle plantar flexion were registered** after SmartOs-driven therapy. In addition, the SmartOs-driven therapy effectively (i) **promoted a more symmetrical gait pattern** by aligning the step and stride lengths of the paretic and non-paretic limbs; and (ii) contributed to an **increase in gait speed**. Despite the promising results, **more therapy sessions should be carried out to maintain the acquired effects in the long term.**

Based on these above-mentioned findings, this study also shows biomechanical and functional improvements in joints and muscles that were not the direct target of the assistance provided. This means that, despite the fact that the assistance was focused on the paretic ankle joint and the muscles responsible for its movement, **physiological and kinematic improvements were found in the knee and hip joints of the paretic limb and the ankle, knee, and hip joints of the non-paretic limb.**

In addition, both post-stroke patients **felt motivated, more symmetrical, and more aware of their posture when using the SmartOs system.**

In conclusion, the **SmartOs system showed promising results in improving motor control and functional mobility in post-stroke patients.** The difference in results between the control strategies highlights the importance of personalized rehabilitation approaches tailored to the specific needs and conditions of each patient. Despite the promising achievements, there is room for improvement. This study is limited to the sample size and training duration. In this connection, further research with larger cohorts of participants and higher duration will help to understand the long-term effects and maintenance of therapy benefits.

8. CONCLUSIONS

This chapter provides concluding remarks and highlights the main contributions by contextualizing the results of the previous chapters. It also outlines future directions to enhance the technological and clinical value of the SmartOs system, as well as opportunities for further technical improvements.

8.1 CONCLUDING REMARKS

This Ph.D. thesis proposes advances in the SmartOs system, an active and intelligent lower limb orthotic system, to tackle the current challenges in user-oriented gait rehabilitation. The advances in the SmartOs system have been developed and experimentally evaluated with the purpose of serving as a personalized assistive solution for post-stroke patients with motor disabilities and spastic gait.

In Chapter 2, KPI 1 and Objective 1 were achieved by detailing that the main effects of using wearable assistive devices during post-stroke gait rehabilitation therapies include improvements in gait speed, balance, walking distance, gait symmetry, and muscle strength. These positive outcomes result from rehabilitation sessions that typically last around 38.3 minutes per session, performed three times a week for an average of fifteen sessions.

Chapter 3 demonstrated how SmartOs integrates wearable sensor systems, gait analysis tools, and assistance control strategies in an interoperable way, enabling dynamic adaption of the AO's assistance based on real-time assessment of the user's physiological needs and locomotion intentions. The expandability of the SmartOs system, defining new sensing and assistance functionalities (Objective 2) was successfully achieved by respecting the hierarchical and modular architecture of the system.

In Chapter 4, the MuscLab system was successfully developed to monitor and differentiate muscle contractions in different muscle groups in individuals with different anthropometries (Objective 3). From a benchmarking analysis with commercial systems, KPI 2 was achieved since very strong correlations between the MuscLab and the *tibialis anterior* and *gastrocnemius lateralis* EMG signals were verified. These results confirm the effectiveness of the MuscLab system, as a stand-alone, self-calibrated, low-cost, wearable sensor system, in monitoring muscle contraction.

Additionally, Chapter 5 presents two significant contributions to the state-of-the-art: (i) investigating the optimal fusion between sensor data and classification algorithms to predict four LMs (St, LGW, SA, and SD); and (ii) developing, validating, and integrating an automatic LM decoding tool into the SmartOs system. These contributions concretize KPI 3 and Objective 4. This thesis concludes that (i) using RMS EMG features alone is insufficient for effective LM decoding, and (ii) incorporating right and left thigh and shank segment angles as input to an LSTM model yields the best LM decoding performance. The proposed tool demonstrated a highly accurate performance in both offline and online testing with healthy participants and a post-stroke patient while maintaining a low computational load. In addition, the tool

proved to be robust across different gait speeds and scenarios. These results highlight the potential of the developed LM decoding tool to advance LM-driven trajectory control strategies, enabling wearable assistive devices to timely adapt their assistance in real-time based on the decoded LMs.

Chapter 6 discloses that the proposed closed-loop AAN control strategies to adaptively and safely generate personalized assistive commands according to the user's real-time needs and locomotion intentions were successfully implemented, concretizing KPI 4 and Objective 5. The AAN LM-driven trajectory control revealed that users were assisted by the SmartOs system, showing that the wearable assistive device can timely and automatically adjust its assistance throughout the entire gait cycle according to the predicted LM. The control was tested for different gait speeds and different scenarios and offered a high performance in all conditions.

Furthermore, this thesis addressed a gap in the current literature by proposing an AAN EMG-based control strategy to automatically assist the ankle joint throughout gait according to the user's muscular performance evaluated by EMG signals. The experimental results showed that the assistance of the SmartOs system was automatically adapted according to the participant's involvement during the entire gait cycle. The device increased its level of assistance as the user's level of participation in walking decreased, and vice versa.

This thesis also advanced by proposing an AAN HITL control capable of reducing the user's energy expenditure by adjusting the control parameters during gait. Based on a 20-minute optimization algorithm, the proposed control found the optimal control parameters that reduced the user's energy expenditure. The innovation derived from this is that it is the first work to develop an AAN HITL control strategy to assist the ankle joint using an electric motor-based actuator with a gear-based transmission.

Chapter 7 revealed that the SmartOs system showed promising results in improving motor control and functional mobility in post-stroke patients, achieving KPI 5 and Objective 6. Through longitudinal case studies evaluating the effects of a trajectory-tracking position, adaptive impedance, and AAN EMG-based control strategies, general improvements were verified at the physiological and kinematic levels regarding ankle biomechanics. Improvements in gait symmetry and gait speed were also verified. Although the rehabilitation therapy was focused on the ankle joint, physiological and kinematic enhancements were noticed at other lower limb joints and muscles, revealing the potential of the rehabilitation therapy with the SmartOs system. Nonetheless, retention assessments highlighted the necessity for continuous therapy to maintain gains in muscle activity and functional mobility.

The overall results of experimental validations conducted on healthy participants demonstrated the effective functionality of the SmartOs system. The system successfully addressed the locomotor,

muscular, and metabolic needs of the participants, by providing personalized gait assistance and achieving a Technology Readiness Level (TRL) of 4. At this stage, the SmartOs system is fully operational and has already demonstrated a positive impact on two post-stroke patients with varying degrees of lower limb disability. Further, longitudinal studies are required to assess the effects of the system on neurologically impaired individuals, with the aim of progressing to TRL 5.

8.2 RESEARCH QUESTIONS

The findings of this research allow the following RQs to be answered:

- **RQ1: How can e-textiles be used to monitor the muscular contraction of several muscles simultaneously?**

This RQ is related to **Objective 3** and it is addressed in **Chapter 4**. E-textiles can be used to monitor the muscle contraction of multiple muscles simultaneously by **incorporating piezoresistive textile sensors into flexible and elastic bands**.

These sensors can detect muscle contractions by measuring changes in muscle bulging as the muscles contract. The proposed MuscLab system demonstrated that such e-textiles could effectively monitor and discriminate the activity of different muscle groups in individuals with different anthropometries. The system showed high repeatability, prompt response to different motion cadences, and strong correlations with traditional EMG measurements, confirming its potential for accurate and simultaneous monitoring of muscle contraction across multiple muscle groups.

- **RQ2: What fusion of sensor data and AI algorithms yields the most effective decoding of daily LMs using AO considering time and accuracy?**

This RQ is related to **Objective 4** and it is addressed in **Chapter 5**. The findings of this research suggest that the use of an **LSTM classifier fed by kinematic information from thigh and shank segment angles with their derivatives yielded the most accurate and timely tool to decode daily LMs (St, LGW, SA, and SD)** when using wearable assistive devices. This combination yielded the highest accuracy (average 0.982 ± 0.009) and low computational load (1.58 ± 0.42 ms). This setup was effective across different gait speeds, scenarios, and user conditions, including both healthy and post-stroke participants. It also showed strong generalization capabilities and robustness in predicting LMs, with an average prediction time of 482 ± 227 ms.

- **RQ3: How to select the control parameters of wearable assistive devices to provide AAN training according to the user's physiological needs and locomotion intentions?**

This RQ is related to **Objective 5** and is answered in **Chapter 6**. In this Ph.D thesis, three AAN control strategies were proposed, developed, integrated, and validated into a wearable assistive device (SmartOs system), to provide assistance according to the user's needs and locomotion intentions. An **AAN LM-driven trajectory control** was developed to adapt the assistance of the device, by timely changing the reference trajectory of the system considering the LM decoded in real-time. Attention has been paid to the critical instant for predicting LMs and the instant at which the SmartOs system assistance should be adapted. Furthermore, an **AAN EMG-based control** was developed to understand how much assistance the user requires, in real-time, to complete the desired motion (in this case, walking). This control system has been carefully designed to take into account the user's level of participation through their EMG signals from the *tibialis anterior* and *gastrocnemius lateralis* muscles, in order to assist the user when and as much as necessary, without overcompensating. Finally, the **AAN HITL control** was developed with the purpose of adapting the system's control parameters in order to reduce the user's energy expenditure. For that, an AI-based regressor was employed to quantify the user's energy expenditure every 10 seconds. According to the energy expenditure and the human-exoskeleton interaction (interaction torque), an optimizer (CMA-ES) was implemented to adjust the control parameters (magnitude of the plantar flexion and dorsiflexion torque values) in an attempt to reduce the user's energy consumption.

- **RQ4: What are the spatiotemporal, physiological, and kinematic effects of rehabilitation therapies applied to post-stroke patients using the SmartOs system?**

This RQ is related to **Objective 6** and it is addressed in **Chapter 7**. The effects of using the SmartOs system in rehabilitation therapies for post-stroke patients were evaluated through two case studies, each with different ankle deformities. **Sessions were conducted twice weekly over fifteen sessions**, using three control strategies: **trajectory-tracking position control, adaptive impedance control, and AAN**

EMG-based control. For a post-stroke patient with **equinovarus deformity**, the SmartOs-driven therapy allowed (i) increased *tibialis anterior* muscle contraction, particularly with the AAN EMG-based control; (ii) reduced *gastrocnemius lateralis* contraction, especially with trajectory-tracking position control; (iii) improved ankle dorsiflexion with trajectory-tracking and adaptive impedance controls; (iv) increased ankle plantar flexion only with trajectory-tracking position control; (v) a more symmetrical gait pattern with step and stride lengths becoming balanced between paretic and non-paretic limbs; and (vi) increased gait speed. For a post-stroke patient with **equinus deformity**, the SmartOs-driven therapy permitted (i) the strengthening of the *tibialis anterior* muscle post-training; (ii) the immediate increase in ankle plantar flexion with trajectory-tracking and adaptive impedance controls; (iii) the long-term increase in ankle dorsiflexion noted at follow-up; (iv) a more symmetrical gait pattern, with step and stride lengths aligning between paretic and non-paretic limbs; and (v) increased gait speed. Moreover, the SmartOs system led to improvements not only in the targeted ankle joint but also in other joints and muscles of both limbs. Post-stroke patients showed high motivation to use the SmartOs system, expressed interest in further sessions, and progressive improvements in movement fluidity. They also noted improved symmetry and body awareness in their ankle, knee, and hip joints and overall posture. Despite immediate benefits, **maintaining long-term improvements requires ongoing therapy**, highlighting the need for **personalized and sustained rehabilitation strategies**.

8.3 FUTURE DIRECTIONS

Future directions for improving the SmartOs system should be focused on: (i) optimizing the MuscLab sensor design for different parts of the human body; (ii) using the MuscLab integrated IMU sensor to compute joint and segment angles; (iii) using the MuscLab sensor for muscle fatigue estimation and LM decoding; (iv) conducting additional real-time validation procedures of the developed LM decoding tool with more participants, including both able-bodied individuals and those with varying degrees of neurological impairments; (v) extending the decoding capabilities to other LMs, particularly RA and RD, and transitions; (vi) improving the prediction performance for LGW-St transitions to increase the *update time in advance*; (vii) conducting more validation steps of the AAN control strategies, with a focus on assessing the potential of each assistive control strategy;

(viii) conducting randomized controlled trials with larger cohorts of post-stroke patients to understand the short- and long-term effects and maintenance of a SmartOs-driven therapy.

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