

# Real-Time Control of Ankle Orthosis Assistance Using a Locomotion Mode Prediction Tool

Luís Moreira<sup>1b</sup>, *Student Member, IEEE*, Joana Figueiredo<sup>1b</sup>, *Member, IEEE*,  
and Cristina P. Santos<sup>1b</sup>, *Member, IEEE*

**Abstract**—Robotic assistive devices have been equipped with locomotion mode (LM) decoding tools to adapt their assistance according to the user's locomotion needs. However, most of the LM decoding tools are insufficient to predict the upcoming LM in advance; and do not consider the typically slow speeds of neurologically impaired users. This study aims to address these shortcomings by introducing an LM decoding tool to predict, in real-time, four LMs (standing, level-ground walking, stair descent, and stair ascent) when using a robotic assistive device (SmartOs system) at slow speeds. Thigh and shank segment angles feeding a Long Short-Term Memory provided the highest performance (accuracies of 98.6% and 97.2%, for able-bodied and stroke subjects, respectively). An LM-driven position control strategy was developed to assist the users based on the decoded LM. Real-time evaluations were performed under different speeds (self-selected and controlled), scenarios (indoor and outdoor), and assistance modes (zero-torque and LM-driven position controls). The proposed LM decoding tool showed low computational loads ( $1.58 \pm 0.42$  ms). The SmartOs system was able to predict and adapt its assistance by  $295 \pm 170$  ms before the user entered the new LM. The proposed control strategy is a step towards LM-based assistance for stroke patients.

**Index Terms**—Assistive control strategies, deep learning, exoskeletons, motion intention, wearable sensors.

Received 14 October 2024; revised 30 January 2025 and 24 June 2025; accepted 3 August 2025. Date of publication 29 August 2025; date of current version 2 December 2025. This article was recommended for publication by Associate Editor Q. Wang and Editor P. Dario upon evaluation of the reviewers' comments. This work was supported by the *Fundação para a Ciência e Tecnologia* (FCT) through the Scholarship under Grant 2020.05711.BD, through the Stimulus of Scientific Employment under Grant 2020.03393.CEECIND, and through the National Support to Research and Development Units Grant under Project UIDB/04436/2020 and Project UIDP/04436/2020. (Corresponding author: Luís Moreira.)

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Comissão de Ética para a Investigação em Ciências da Vida e da Saúde (CEICVS)-University of Minho.

Luís Moreira is with the Center for MicroElectroMechanical Systems, University of Minho, 4800-058 Guimarães, Portugal (e-mail: luís.lihtss@gmail.com).

Joana Figueiredo is with the Center for MicroElectroMechanical Systems and the LABBELS—Associate Laboratory, University of Minho, 4800-058 Guimarães, Portugal (e-mail: joana.figueiredo@dei.uminho.pt).

Cristina P. Santos is with Center for MicroElectroMechanical Systems and the LABBELS—Associate Laboratory, University of Minho, 4800-058 Guimarães, Portugal, and also with the 2CA-Braga, Hospital of Braga, 4700-099 Braga, Portugal.

This article has supplementary downloadable material available at <https://doi.org/10.1109/TMRB.2025.3604135>, provided by the authors.

Digital Object Identifier 10.1109/TMRB.2025.3604135

## I. INTRODUCTION

INDIVIDUALS with preserved lower limb mobility adapt their gait patterns for efficient ambulation across various locomotion modes (LMs). As outlined in the study [1], LMs can be classified into static and dynamic tasks. Static tasks involve sitting (Sit) or standing (St). In contrast, dynamic tasks encompass continuous activities (like level-ground walking (LGW), stair descent (SD), stair ascent (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 [2].

Robotic assistive devices, including prostheses, orthoses, and exoskeletons, have been equipped with LM decoding tools to adjust assistance based on the decoded LMs [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14]. However, according to [1], [9], LM decoding with active orthotic and exoskeleton systems, which are the focus of this work, differ fundamentally from prostheses or non-assisted conditions due to: (i) distinct sensor placements in exoskeletons; and (ii) unique human-robot interaction dynamics. Although high accuracies (ACCs) have been reported (ranging from 93.2% to 99.7% [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14]) in decoding different LMs, the timing of LM decoding 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 [3], [7], [8], [9], [10], [11], [13], [14]. 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 [15], [16]. Therefore, as suggested in [5], [6], [17], 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 [5], [6], [17].

In addition to the ability to predict LMs, robotic assistive devices should also be capable of adapting their assistance based on the decoded LM. Among the reviewed studies [3],

[4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], only [6], [12], [13] implemented adaptive assistance based on the decoded LM, using torque control strategies. However, these implementations had notable limitations: (i) assistance was limited to the stance phase [12]; (ii) high response delays (ranging from 300 to 1000 ms) were reported between LM decoding and actuator response [13]; and (iii) the evaluated gait speeds exceeded those typically adopted by individuals with lower limb impairments [6], [12].

Furthermore, it is still unclear which sensor data should be fused and which classification algorithm to use for improving LM prediction. Especially when these LM decoding tools are integrated into robotic devices. In such cases, electromyography (EMG) [7], [10], [11], kinematic [3], [4], [8], [9], [12], [13], [14], and depth (RGBD cameras) [5], [6] sensors have been widely explored to feed LM decoding tools, achieving highly accurate performances (ACC ranging from 93.2% to 99.7%).

With respect to EMG signals, studies have employed (i) raw EMG signals [11]; (ii) time-domain features (such as mean absolute value, root mean square (RMS), waveform length, slope sign changes, and zero-crossing) [7]; (iii) frequency-domain (like mean power frequency and median frequency); and (iv) time-frequency-domain features [10]. 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) provided the highest ACC (99.7%) in decoding LMs [11]. Regarding the kinematic sensors, studies have explored lower limb joint angles [8], [14], and segment angles [3], [4], [8], [9], [12], [13]. From the literature, we observed that the thigh and shank segment angles are the most used kinematic data to recognize LMs [3], [4], [9], [12], [13]. These data have been used with (i) Support Vector Machine models [4]; (ii) Finite State Machine models [8]; (iii) Multilayer Feedforward Neural Networks [3], [9]; (iv) fuzzy-logic methods [13]; and (v) a combination of Support Vector Machine and Finite State Machine models [12]. Considering the depth sensors, studies have employed three-dimensional point cloud with a CNN for LM decoding [5], [6].

In summary, while the reviewed studies [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14] are capable of decoding various LMs, many existing LM decoding tools integrated into robotic assistive devices present several limitations. Specifically, these tools (i) cannot decode several LMs simultaneously with a single decoding tool [12]; (ii) exhibit high recognition delays, classifying the LM only after the user has already transitioned to it [3], [7], [8], [9], [10], [11], [13]; (iii) consider self-selected and/or fixed speeds of able-bodied participants (typically above 2.7 km/h) [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [14], which results in biomechanical differences of those observed in typically slower gait speeds of individuals with lower limb disabilities; and (iv) are not tested in scenarios different to those in which the tool was trained [3], [4], [7], [8], [9], [10], [11], [12], [13], [14].

This study addresses the aforementioned challenges by introducing an automatic deep learning (DL) tool designed to predict both static and dynamic LMs (including St, LGW,

SD, and SA), during the use of a robotic assistive device (SmartOs system [18]). The study advances the current state-of-the-art by (i) investigating the most appropriate sensor data (between kinematic and EMG data) and DL algorithms for predicting LMs at slow speeds, considering the preferred gait speeds of individuals with lower limb impairments (below 2.7 km/h) [19]; and (ii) proposing an assistive control strategy to adapt the assistance of the SmartOs system according to the predicted LM. The DL tool was tested on both able-bodied participants and a 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. We implemented our solution such that the SmartOs system is able to predict the upcoming LM and timely adapt its assistance according to the LM decoded while achieving an ACC close to 99.7% (the highest ACC identified in the reviewed studies [11]).

## II. LOCOMOTION MODE DECODING TOOL

### A. SmartOs Description

The SmartOs system features a non-centralized architecture structured as a modular and hierarchical framework, organized into high-, mid-, and low-levels, as proposed in [20] (Fig. 1).

The framework includes (i) an Android application; (ii) a Central Control Unit (CCU); (iii) two development boards; (iv) an active ankle orthosis; and (v) a power supply. For user comfort and practicality, the CCU, the development boards, and the power supply are arranged within a backpack housing.

The system is configured using the Android application, which defines the user's parameters, assistive control strategies, gait analysis tools, and sensor systems to be used. The system configuration is transmitted to the CCU via Bluetooth protocol.

The CCU, executing high-level controls at 100 Hz, is implemented in a UDOO X86 computer (2.24 GHz and 4.0 GB RAM). The two development boards, the STM32F4-Discovery boards (STMicroelectronics, Switzerland), communicate with the CCU through a UART interface. The development boards encompass (i) a Wearable Motion LAB, facilitating real-time data acquisition from the InertialLab system (comprising seven 6-axis IMUs (MPU-6050) [21]), and the wireless 8-channel surface EMG system (Trigno – Delsys, Massachusetts, USA) [22]; and (ii) a Low-Level Orthotic System that manages the mid- and low-level controllers and interfaces with the ankle orthosis (Exo-H2, by Technaid, Madrid, Spain [23]) through the Control Area Network (CAN) protocol.

The right ankle orthosis incorporates an electric actuator (EC60 100W Flat Brushless, Maxon, Germany) coupled to a gearbox (CSD-20-160-2A-GR, Harmonic Drive, Japan) with a ratio of 160:1. This device can deliver an average torque of 35 N.m and a peak torque of 180 N.m [23]. More information about the right ankle orthosis can be found in the study [23].

The power supply system features a lithium iron phosphate battery (LifePO4) with a voltage of 22.4V. A hardware interface supplies 12V to the CCU and 5V to the two development boards.

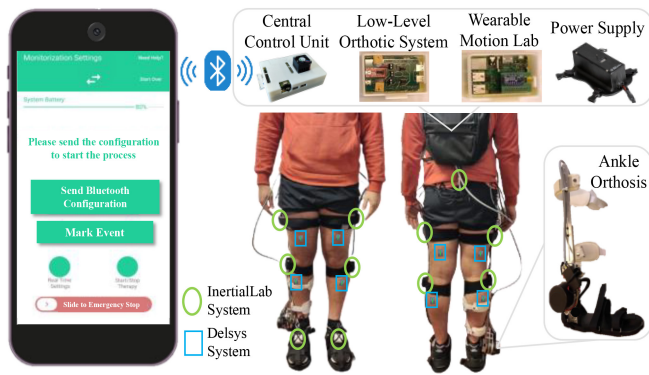


Fig. 1. A male participant instrumented with the SmartOs, Delsys, and InertialLab systems.

### B. Data Acquisition

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

- 1) *Participants*: The study involved 15 able-bodied participants (8 males and 7 females) with an average age, body mass, and body height of  $25.0 \pm 2.71$  years old,  $67.9 \pm 13.3$  kg, and  $171.0 \pm 8.14$  cm, respectively. 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).
- 2) *Instrumentation and Data Collection*: The wireless 8-channel surface EMG system (Trigno – Delsys, Massachusetts, USA) was used to capture EMG signals from eight lower limb muscles: *tibialis anterior*, *gastrocnemius lateralis*, *biceps femoris*, and *vastus lateralis* of both lower limbs, as depicted in Fig. 1, in blue color. The eight EMG sensors were placed over the muscles, following the recommendations of SENIAM [24]. The RMS of EMG signals was acquired at 100 Hz. Moreover, the participants were instrumented with seven IMUs of the InertialLab system in the pelvis and lower limb segments (right and left thighs, shanks, and feet), as depicted in Fig. 1, in green color. The system recorded 3D acceleration, 3D angular velocity, and sagittal angles of the lower limb segments (pelvis, thighs, shanks, and feet), and sagittal lower limb joint angles (hips, knees, and ankles) at 100 Hz. The study [21] details the segment and joint angles computation.
- 3) *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 [25]. Subsequently, we equipped the participants 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 tasks while the ankle orthosis operated in zero-torque control, as depicted in Fig. 2.

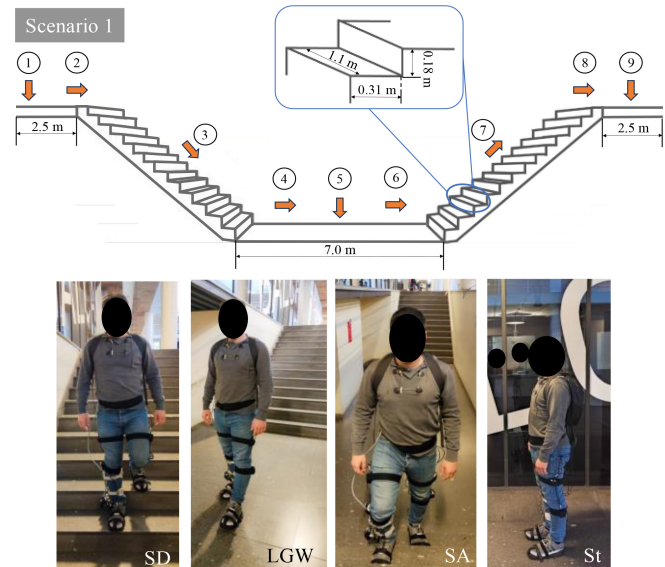


Fig. 2. A random participant performing the four LMs (St, LGW, SD, SA) in the first scenario. Positions (1) and (9) denote the starting and ending positions, respectively.

The tasks 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 [26]. This range falls in the slow speeds typically adopted by individuals with motor disabilities [19].

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 [27]. Second, the ankle orthosis is mechanically limited to a maximum dorsiflexion angle value of 20 degrees (a value easily exceeded when descending stairs with the non-instrumented leg (left leg) being the first to advance).

- 4) *Data Labeling*: A researcher annotated the transitions between LMs during the protocol, from toe-off to the critical instant. The critical instant was defined as the

moment when the participant placed the leading foot on the new LM. This definition ensures consistency across transitions and aligns with control requirements for assistive devices, which must adapt their assistance prior to this instant, so that the appropriate support is active upon entry into the new LM [4]. Transitions were marked using the Android Application of the SmartOs system (via the “Mark Event” button, as illustrated in Fig. 1) to ensure synchronization with the other collected data. Subsequently, all trials were manually reviewed by two researchers to verify labeling accuracy. At this stage, four classes were defined, 0 – St, 1 – LGW, 2 – SD, and 3 – SA.

### C. Data Preparation

Considering the reviewed studies [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], several types of data were employed in decoding LMs, namely features from EMG signals [7], [10], segment [3], [4], [9], [12], [13] and joint angles [8], [14], and depth sensors [5], [6].

There is still no consensus on what type of data yielded more accurate LM decoding. Depth sensor data were not used in this study due to their high processing requirements [5], [6]. Thus, we compared the LM decoding performance using four types of sensor data: (i) RMS EMG normalized by MVC (one of the most used EMG features [7], [10]); (ii) the segment angles (pelvis, 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 pelvis, thigh, shank, and/or foot segments. In the segment and joint angle data types, we computed their first and second-order derivatives, since we found in empirical tests that these variables improved the model’s performance. 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 (1) presents an example of computing the magnitude of 3D acceleration data ( $|a|$ ), in which  $a_x$ ,  $a_y$ , and  $a_z$  represent the acceleration measured in the  $x$ -,  $y$ -, and  $z$ -axes, respectively.

$$|a| = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (1)$$

A total of 38 inputs (see Table I) were created and organized into sequences with  $X$  time-ordered samples (by time and participant) and  $Y$  input features.

### D. Classification Models

In the scope of this study, we explored Long Short-Term Memory (LSTM), CNN, and Transformer since these models revealed high generalization ability and high performances in previous studies and are adequate for time series [28], [29], [30]. 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).

TABLE I  
IDENTIFICATION OF THE TYPE OF INPUTS USED IN THIS STUDY. 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                |
| 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).

Several empirical analyses were conducted to find the best LM decoding tool. Regarding LSTM, we 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 the three DL models, we explored the (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, we utilized (i) the adaptive moment estimation optimization algorithm to optimize the parameters of the neural networks, including weights and biases [31]; (ii) the focal cross-entropy loss to address potential class imbalance [32]; 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 [33], [34].

To determine the optimal hyperparameters and the best LM decoding tool, a leave-one-subject-out cross-validation

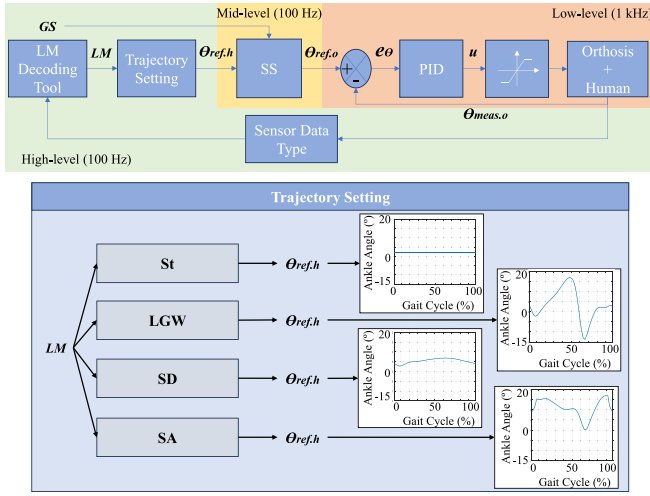


Fig. 3. Proposed LM-driven position control.  $GS$  is the gait speed.  $LM$  is the predicted LM.  $\theta_{ref,h}$  and  $\theta_{ref,o}$  are the human and orthosis reference ankle angles, respectively.  $\theta_{meas,o}$  is the measured ankle angle.  $e_\theta$  is the orthosis position error.  $u$  is the Proportional-Integral-Derivative (PID) command.  $SS$  is a speed scaling block achieved by (2).  $PID$  stands for the PID controller.

(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.

### III. ASSISTIVE CONTROL STRATEGY

We developed a hierarchical three-level control strategy to adapt the joint angle position of the SmartOs system according to the decoded LM (St, LGW, SA, or SD). Fig. 3 presents the proposed LM-driven position control.

#### A. High-Level Controller

The high-level runs the LM decoding tool. As depicted in Fig. 3, new input data arrives at the LM decoding tool (*LM Decoding Tool* block) at 100 Hz. 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 were obtained from the dataset collected for developing the LM decoding tool.

#### B. Mid-Level Controller

The mid-level controller contains the *Speed Scaling* block and operates at 100 Hz. It receives the  $\theta_{ref,h}$  generated by the

*Trajectory Setting* block and the gait speed ( $GS$ ). The  $\theta_{ref,h}$  is scaled to the low-level control frequency (1 kHz), through Equation (2) found in the study [35].

$$\text{Speed Scaling} = 107.31 - 34.62 \times GS \quad (2)$$

#### C. Low-Level Controller

The low-level controller works at 1 kHz. It compares the  $\theta_{ref,o}$  with the measured ankle angle ( $\theta_{meas,o}$ ), providing the orthosis position error ( $e_\theta$ ). The  $e_\theta$  is then fed into the Proportional-Integral-Derivative (PID) controller with proportional, integral, and derivative gains set to 95, 1.5, and 1.5, respectively. The PID controller (*PID* block) generates a 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.

### IV. FULL SOLUTION EXPERIMENTATION

The LM decoding tool and the LM-driven position control strategy were tested under real-time procedures, considering different gait speeds and scenarios.

#### A. Participants

To validate the LM decoding tool in real-time, we included three participants: two able-bodied participants (one male and one female with an average age, body mass, and body height of  $26.0 \pm 1.00$  years old,  $76.5 \pm 6.5$  kg, and  $167.5 \pm 2.5$  cm) and one female participant who 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; Fugl-Meyer Assessment - Lower Extremity: 32). It is noteworthy that the DL model training process did not involve these participants. The LM-driven position 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. Protocol

In the beginning, participants were instrumented with the sensor configuration that provided the best classification performances, 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, two different experiments were conducted with the SmartOs system. The first experiment was focused on the real-time validation of the LM decoding tool by using the SmartOs operating under zero-torque control. In the second experiment, we validated both the LM decoding tool and the LM-driven position control strategy in real-time (i.e., SmartOs was controlled by the LM-driven position control). In both experiments, participants walked at different gait speeds, as summarized in Table II. The selected gait speeds cover those preferred by stroke patients, i.e., less than 2.7 km/h.

TABLE II  
IDENTIFICATION OF THE REAL-TIME TESTS PERFORMED BY  
ABLE-BODIED PARTICIPANTS AND STROKE PATIENT

| Subject     | Control Mode               | Scenario | Gait Speed    |
|-------------|----------------------------|----------|---------------|
| Able-bodied | Zero-torque Control        | 1        | Self-selected |
|             |                            | 2        | 35 bpm        |
|             |                            | 3        | 40 bpm        |
|             | LM-driven Position Control | 1        | 45 bpm        |
|             |                            | 2        | 50 bpm        |
|             |                            | 3        | 1.0 km/h      |
| Stroke      | Zero-torque Control        | 1        | 1.2 km/h      |
|             |                            | 2        | 1.4 km/h      |
|             |                            | 3        | 1.6 km/h      |
| Stroke      | Zero-torque Control        | 2        | Self-selected |

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 scenarios and speeds.

The first scenario (Fig. 2) consists of the same terrain 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 (Fig. 4 – left view) represents another indoor scenario composed of 8 steps with the same dimensions as scenario 1. The third scenario (Fig. 4 – 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 (Section II). For the second and third scenarios, participants completed a continuous circuit of nine task sequences, as depicted in Fig. 4, 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 degrees, 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 sequence number 5, the turning task was ignored, 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 Android Application of the SmartOs system (Fig. 1). These events were inspected by two additional researchers to ensure accuracy in labeling the transition instants.

### C. Evaluation Metrics

We assessed four metrics, namely, (i) ACC and success rate per class to evaluate the performance of the LM decoding tool; and (ii) *computational load* (in ms) and *update time in advance* (in ms and as a percentage of the gait cycle) to assess the performance of the LM-driven position control strategy.

The *computational load* (in ms) denotes the time necessary for the LM decoding tool to classify the LM upon receiving new data. The *update time in advance* (in ms) is determined

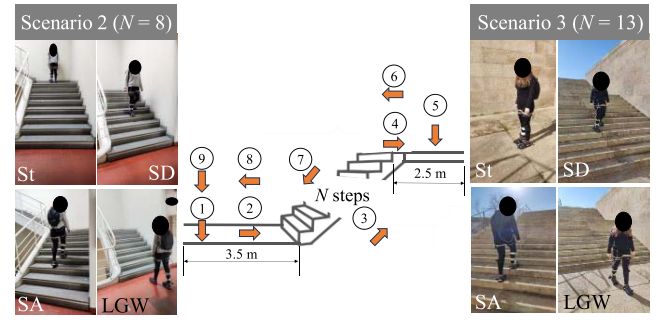


Fig. 4. An able-bodied test participant performing the four LMs (St, LGW, SD, SA) in the second scenario (left view) and in the third scenario (right view). Positions (1) and (9) denote the starting and ending positions, respectively.

by Equation (3), in which (i)  $T_{critical}$  represents the critical instant; (ii)  $T_{prediction}$  is the instant in which the LM decoding tool performed a classification; and (iii) *latency* corresponds to 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  $260 \pm 0.27$  ms [36]. 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.

$$Update\ Time\ in\ Advance\ (ms)$$

$$= T_{critical} - (T_{prediction} + latency) \quad (3)$$

## V. RESULTS

### A. Input Data Analysis

A total of 954,298 samples were collected to train the DL models, distributed as follows: 22% for the St task, 30% for the LGW, 23% for the SD, and 25% for the SA. Table A1 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 below  $0.794 \pm 0.078$ ). Among these data, we 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 between 0.915 and 0.954) 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 between 0.976 and 0.980).

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 between 0.482 and 0.900). 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 between 0.968 and 0.979), and from the thigh and shank IMUs specifically for the CNN (average ACC of  $0.975 \pm 0.007$ ).

Finally, when considering the data type combining the segment angles along with their derivatives, for all DL models, we verified that using (i) the pelvic segment angles and their derivatives reduced the models' performance (average ACC between 0.732 and 0.794); and (ii) the thigh and shank segment angles and their derivatives improved the model performance (average ACC between 0.979 and 0.982).

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.

### B. DL Model Analysis

The results in Table A1 indicate that the highest performance was achieved by the LSTM model, which was fed with segment angles, angular velocities, and angular accelerations of both thighs and shanks (average ACC of  $0.982 \pm 0.009$ ). This LSTM architecture comprised two *LSTM layers* with 20 neurons each, 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*. A *batch size* of 64, a *sequence length* of 140, and *z-score normalization* were used to optimize its performance.

The LSTM model outperformed the CNN and Transformer models across most input configurations, particularly when fed with joint angles or segment angular data and their derivatives. Fig. 5 – left view illustrates the training and validation loss curves for the LSTM, showing convergence around epoch 60 without overfitting, as the validation loss closely follows the training loss. Additionally, the offline test ACC of the LSTM (0.982) aligns with the LOSOCV results, indicating strong generalization ability. Fig. 5 – right view confirms the accuracy of the model's predictions, as the predicted labels closely match the ground truth labels during testing.

The CNN model also achieved competitive results, with its highest performance being marginally lower than that of the LSTM model (average ACC of  $0.979 \pm 0.008$ ). CNNs were most effective in configurations where segment angular data or joint angular data were provided as input. However, the CNN exhibited slightly higher sensitivity to input variations, as seen in the slightly larger standard deviations compared to the LSTM.

The Transformer model, while capable of achieving high ACC values (up to  $0.980 \pm 0.006$  in its best configuration), demonstrated the weakest overall performance compared to the LSTM and CNN models. Transformers were most effective with input combinations that included segment angular data, but their performance dropped significantly when other types of data, such as EMG, were used.

The comparison of the three DL models highlights LSTM's superior performance and robustness across diverse input configurations. While CNNs occasionally achieved results

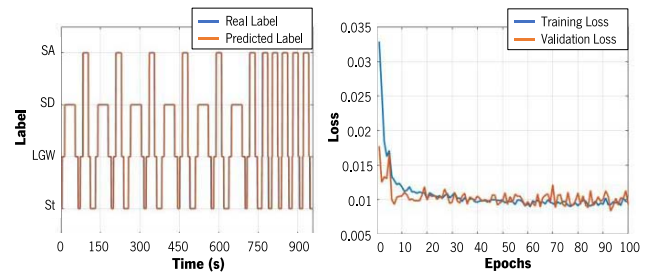


Fig. 5. Training and validation loss obtained during the model training procedure (left view) and offline classification of the LSTM model in the test participant (right view).

comparable to the LSTM in some configurations, they generally exhibited higher variability and slightly lower accuracy. Transformers, on the other hand, showed potential in configurations that included segment angular data but lacked the consistency of the LSTM and CNN models. The results suggest that LSTM's ability to model temporal dependencies in sequential data makes it the most effective architecture to be used as an LM decoding tool.

### C. Full Solution Analysis

The best model found was tested under real-time conditions. A total of 1,067,420 predictions were made during real-time experiments with able-bodied participants. Table III shows the average ACC values across gait speeds, scenarios, and control modes. In general, the results presented in Table III show a high average (above 0.964) and low standard deviation (around 0.010) values for all metrics, achieving an average ACC of  $0.986 \pm 0.004$ . In addition, these results indicate that the proposed LM decoding tool is robust to different speeds (controlled and self-selected speeds), scenarios (indoor and outdoor, variable stair dimensions), and control modes (zero-torque and LM-driven position controls) since the achieved metrics for each speed, scenario, and assistance mode are quite close.

Moreover, the LSTM model made 7,718 predictions in real-time with the stroke patient as the experiment with this participant was performed once at only one speed (self-selected), in a single scenario (scenario 2), and with the active orthosis operating under the zero-torque control. In this case, the LSTM model achieved an ACC of 0.972.

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

In terms of *computational load*, the average time per prediction was around  $1.58 \pm 0.42$  ms. This indicates that from the moment the LM decoding tool receives the InertialLab data (the right and left thigh and shank segment angles), calculates

TABLE III  
ONLINE TEST METRICS FOR ABLE-BODIED PARTICIPANTS

| Control Mode                 | Scenario | Speed    | ACC           |
|------------------------------|----------|----------|---------------|
| Zero-torque Control          | 1        | SS*      | 0.990         |
|                              |          | 35 bpm   | 0.989         |
|                              |          | 40 bpm   | 0.989         |
|                              |          | 45 bpm   | 0.991         |
|                              |          | 50 bpm   | 0.989         |
|                              | 2        | SS       | 0.979         |
|                              |          | 35 bpm   | 0.980         |
|                              |          | 40 bpm   | 0.981         |
|                              |          | 45 bpm   | 0.982         |
|                              |          | 50 bpm   | 0.978         |
|                              | 3        | SS       | 0.987         |
|                              |          | 35 bpm   | 0.988         |
|                              |          | 40 bpm   | 0.984         |
|                              |          | 45 bpm   | 0.983         |
|                              |          | 50 bpm   | 0.984         |
| LM-driven Position Control   | 1        | 1.0 km/h | 0.988         |
|                              |          | 1.2 km/h | 0.988         |
|                              |          | 1.4 km/h | 0.990         |
|                              |          | 1.6 km/h | 0.988         |
|                              | 2        | 1.0 km/h | 0.989         |
|                              |          | 1.2 km/h | 0.988         |
|                              |          | 1.4 km/h | 0.989         |
|                              |          | 1.6 km/h | 0.986         |
|                              | 3        | 1.0 km/h | 0.988         |
|                              |          | 1.2 km/h | 0.991         |
|                              |          | 1.4 km/h | 0.989         |
|                              |          | 1.6 km/h | 0.986         |
| Average (standard deviation) |          |          | 0.986 (0.004) |

\*SS means self-selected.

TABLE IV  
SUCCESS RATE (%) PER LM

| Subject     | St          | LGW         | SD          | SA          |
|-------------|-------------|-------------|-------------|-------------|
| Able-bodied | 93.8 ± 2.17 | 97.3 ± 1.05 | 99.1 ± 0.49 | 98.9 ± 0.94 |
| Stroke      | 88.9        | 93.5        | 99.5        | 95.7        |

angular velocities and accelerations, and performs an LM classification, the proposed decoding tool typically takes less than 2 ms.

Additionally, Table V summarizes the *update time in advance*, in milliseconds, and as a percentage of the gait cycle. From the results exhibited in Table V, the St-LGW transition represents the transition that is earliest detected and assisted, i.e., with higher *update time in advance* before reaching the upcoming LM, presenting average values of  $626 \pm 242$  ms ( $81.8 \pm 7.98\%$  of the previous gait cycle). On the other hand, the LGW-St corresponds to the transition detected and assisted with the lower *update time in advance* ( $80 \pm 352$  ms, corresponding to  $97.8 \pm 13.6\%$  of the previous gait cycle).

Fig. 6 presents a graphical representation of the SmartOs performance during the LGW-SA transition. From Fig. 6, it is possible to verify that the instant in which the LM decoding tool performed a new classification and the instant in which the SmartOs system adapted its assistance occurred before the critical instant.

Additionally, Fig. 6 shows an error of 23% and a delay of 260 ms between the reference and the measured ankle joint angles. These values are consistent with those reported in the study [37], which observed an error of 27% and a

TABLE V  
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        |
|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| 626<br>(242)   | 302<br>(237)   | 268<br>(275)   | 319<br>(288)   | 163<br>(221)   | 80<br>(352)    | 295<br>(170)   |
| 81.8<br>(7.98) | 90.7<br>(8.22) | 92.3<br>(8.48) | 91.8<br>(6.16) | 94.2<br>(6.88) | 97.8<br>(13.6) | 91.4<br>(2.40) |

\*The values inside curved brackets represent the standard deviation.

delay of 260 ms. This delay reflects the inherent limitations of PID-based control systems in responding to rapid trajectory changes, particularly during dynamic tasks [37].

## VI. DISCUSSION

This research was carried out in the field of robotic gait assistance with the ultimate goal of assisting impaired subjects in everyday locomotion tasks. This work brings two contributions to the state-of-the-art. First, it studied the best sensor data and classification algorithm to build a 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, i.e., below 2.7 km/h. Second, it developed an LM-driven position control strategy that timely adapts the assistance of an ankle active orthosis (SmartOs system [18]) according to the decoded LM. The applicability of the LM decoding tool and the control strategy were both tested under real-time conditions with two able-bodied participants and one stroke patient, across different speeds (self-selected and controlled), scenarios (indoor and outdoor with stairs and flat floors with different dimensions), and assistance modes (zero-torque and LM-driven position controls).

### A. Input Data Analysis

Thirty-eight input combinations were explored to build a generalized LM decoding tool. The results showed that the use of the RMS EMG data offered the lowest performance ( $0.599 < \text{ACC} < 0.794$ ), regardless of the DL algorithm. Our performances were lower than the ones presented in previous studies [7], [10], [11] ( $0.949 < \text{ACC} < 0.997$ ). This lower performance may be explained by the single use of one time-domain feature (the RMS EMG) whereas previous studies [7], [10], [11] have combined this feature with other EMG features (mean absolute value, waveform length, slope sign changes, and zero-crossing). Moreover, we verified that the exclusive dependence on 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 the literature evidence, since both *rectus* and *biceps femoris* provide a valuable contribution in terms of stability and propulsion during SA and SD tasks [38].

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 exceed the literature findings [14], where the use of hip

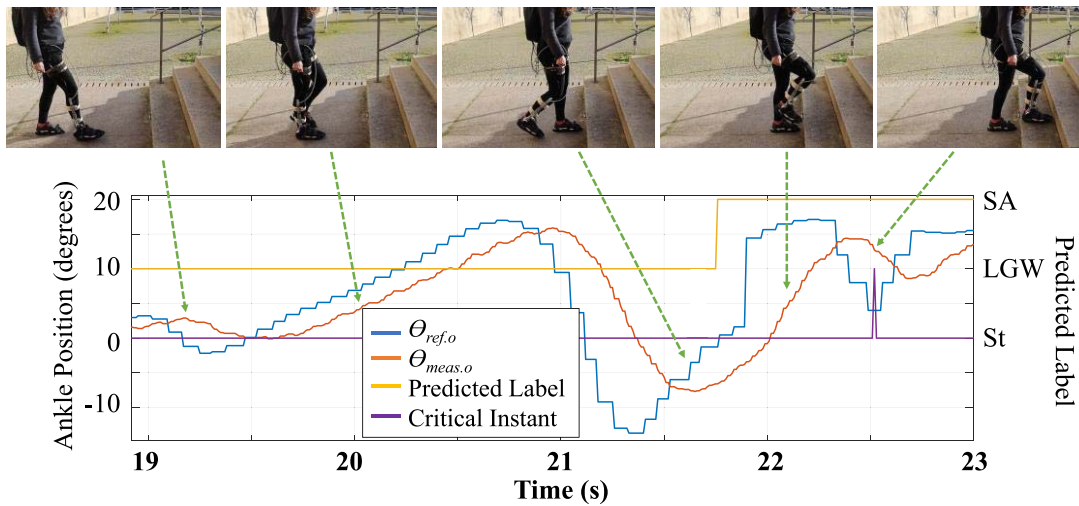


Fig. 6. Example of a transition between the LGW and SA tasks with adaptation of the ankle joint angle trajectory.

and knee joint angles and their derivatives for LM decoding revealed accuracies 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, presents 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 not being 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 [3], [4], [8], [9], [12], [13], [14]. Moreover, the results across DL models 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. So, 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 ( $0.979 < \text{ACC} < 0.982$ ). Our results are aligned with those achieved in studies [4], [12], since the use of thigh and shank segment angles and derivatives revealed accuracies ranging from 0.930 and 0.983.

Overall, there seems to be a tendency to achieve high decoding performances when using kinematic information 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 explained by the high

variation in knee and hip flexion and extension, as well as the range of motion of these joints, across different LMs.

### B. DL Model Analysis

From the benchmark analysis of different data types and DL algorithms, the best LOSOCV results were achieved with an LSTM model fed with thigh and shank segment angles and their derivatives, yielding an average ACC of  $0.982 \pm 0.009$ . Notably, this LSTM model demonstrated strong generalization capabilities across participants, as evidenced by both LOSOCV and offline test results. This architecture consistently outperformed CNN and Transformer models in this study. Moreover, the use of LSTM models for LM decoding with robotic assistive devices has not been reported in the literature [3], [4], [7], [8], [9], [10], [11], [12], [13], [14], marking a novel contribution of this study.

Direct comparisons with literature are challenging due to differences in experimental protocols, datasets, and classified LMs. However, the performance of our LSTM model (average ACC of  $98.2 \pm 0.9\%$ ) surpasses that reported in studies utilizing other methods, including (i) fuzzy-logic methods (93.2%) [13]; (ii) Support Vector Machines (95.5%) [4]; and (iii) Multilayer Feedforward Neural Networks (97.8%) [3].

Additionally, study [12] achieved an average ACC of 98.3% for able-bodied participants and 97.4% for a stroke patient by combining Support Vector Machine and Finite State Machine models. In contrast, our single LSTM model achieved comparable performances, with an ACC of 98.2% for able-bodied participants and 97.2% for the stroke patient. This demonstrates the efficiency of the LSTM model, as it provides state-of-the-art accuracy without the need for hybrid models or additional complexity.

The generalization capabilities of our LSTM model across participants further reinforce its potential as a robust tool for LM decoding in robotic assistive devices. Compared to other approaches in literature, which often require additional user-specific training or exhibit higher sensitivity to input variations, the LSTM architecture effectively captures complex

temporal patterns in kinematic data, making it particularly well-suited for real-world applications.

### C. Full Solution Analysis

The results obtained during real-time test conditions for both able-bodied 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 [12], and it may be related to the asymmetrical and abnormal gait patterns typically performed by stroke patients [39]. Our 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 [3], [4], [8], [9], [12], [13], [14] 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 demonstrated to be robust to different gait speeds, ranging from 1.0 to 1.6 km/h ( $0.988 < ACC < 0.991$ ).

Additionally, in an attempt to advance studies [3], [4], [8], [9], [12], [13], [14], we analyzed the robustness of the model in relation to different scenarios. We tested the model performance in indoor and outdoor scenarios, with different number of steps (8 and 13), with different step dimensions, and with a different order of task execution. The proposed LM decoding tool proved to perform consistently in different scenarios, with accuracies 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 [3], [4], [9], [14]. 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 ( $1.58 \pm 0.42$  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 [40].

It is noteworthy that the assertiveness of LM decoding tools is critical since misclassifications can cause the robotic 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 [16]. Despite the high accuracies reported, most of the reviewed studies recognize the new LM after the user has

already entered on it [3], [7], [8], [9], [10], [11], [13], [14]. The decoding delays typically range from 50.0 to 1897.9 ms after the critical instant.

Only four studies [4], [5], [6], [12] demonstrated the ability to predict specific LMs. Study [4] successfully anticipated the transitions from (i) SA to LGW ( $10.7 \pm 9.88$  ms in advance); (ii) SD to LGW ( $78.7 \pm 130.0$  ms); and (iii) LGW to SA ( $185.3 \pm 56.9$  ms). However, the LGW-SD transition was detected with a delay of  $40.0 \pm 107.5$  ms after the critical instant. Studies [5], [6] predicted transitions between LGW and SA, SD, RA, and RD in both directions. Although the exact timing was not provided for each transition, the authors reported average decoding 1 to 1.2 steps before the critical instant. A limitation was the dependence on a high-performance external laptop for feature processing and LM decoding, which hampers portability. In the study [12], the following transitions were predicted: (i) SD-LGW at  $0.70 \pm 58.7$  ms, (ii) LGW-SA at  $5.40 \pm 74.6$  ms, (iii) SA-LGW at  $46.7 \pm 46.6$  ms, and (iv) LGW-SD at  $78.5 \pm 25.0$  ms. Nevertheless, the study [12] required offline training to create a user-specific decoding model for each participant prior to real-time experiments.

In light of these findings, our LM decoding tool achieves a competitive performance compared to previous studies [3], [4], [7], [8], [9], [10], [11], [12], [13], [14] under test conditions by predicting upcoming LMs with an average *update time in advance* of  $295 \pm 170$  ms. Further, the average *update time in advance* per transition was always positive (ranging from 80 to 626 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 timely decoded and assisted. Translating these results as a percentage of the gait cycle (from 81.8% to 97.8%), we verified that the next LM was decoded, on average, between the mid- and terminal swing of the gait cycle preceding the upcoming LM [41]. This means that, in these gait cycle phases, the SmartOs system was already able to adapt its assistance during the transition of LMs. This was achieved during model training by updating the LM label in the swing phase of the previous stride preceding the upcoming LM, allowing the model to learn anticipatory kinematic patterns. This enabled prediction before foot contact ( $T_{critical}$ ) and timely assistance adaptation.

In addition, the St-LGW transition was decoded and assisted with a higher *update time in advance* ( $626 \pm 242$  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 *update time in advance* ( $80 \pm 352$  ms). The high standard deviation value suggests that, at this transition, the participants were not timely assisted by the SmartOs system in some cases, i.e., the assistance changed 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.

Considering the reviewed studies [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], only [6], [12], [13] adapted device assistance based on the decoded LM. Study [6] implemented a two-level torque control strategy, with LM

TABLE A1

AVERAGE ACC FOR ALL INPUT COMBINATIONS AND DL MODELS. THE BEST AND THE WORST RESULTS FOR EACH DL MODEL ARE COLORED IN **BLUE** AND **RED**, RESPECTIVELY. THE HIGHEST ACC ACHIEVED IS SHADED IN **GREEN**

| ID | LSTM                 | CNN                  | Transformer          |
|----|----------------------|----------------------|----------------------|
| 1  | <b>0.954 (0.023)</b> | <b>0.940 (0.023)</b> | <b>0.915 (0.030)</b> |
| 2  | 0.967 (0.023)        | 0.967 (0.019)        | 0.931 (0.039)        |
| 3  | 0.978 (0.013)        | 0.971 (0.024)        | 0.969 (0.019)        |
| 4  | 0.973 (0.010)        | 0.966 (0.014)        | 0.950 (0.024)        |
| 5  | 0.974 (0.016)        | 0.968 (0.024)        | 0.965 (0.001)        |
| 6  | <b>0.980 (0.010)</b> | <b>0.979 (0.013)</b> | <b>0.976 (0.010)</b> |
| 7  | 0.978 (0.011)        | 0.975 (0.015)        | 0.974 (0.012)        |
| 8  | 0.959 (0.011)        | 0.951 (0.017)        | 0.898 (0.025)        |
| 9  | 0.975 (0.011)        | 0.973 (0.010)        | 0.954 (0.011)        |
| 10 | 0.974 (0.011)        | 0.969 (0.011)        | 0.917 (0.021)        |
| 11 | 0.971 (0.009)        | 0.971 (0.009)        | 0.965 (0.009)        |
| 12 | 0.978 (0.007)        | <b>0.975 (0.007)</b> | 0.964 (0.013)        |
| 13 | 0.970 (0.007)        | 0.962 (0.010)        | 0.951 (0.018)        |
| 14 | 0.961 (0.014)        | 0.954 (0.022)        | 0.930 (0.021)        |
| 15 | 0.974 (0.014)        | 0.970 (0.013)        | 0.921 (0.032)        |
| 16 | 0.970 (0.015)        | 0.974 (0.007)        | 0.939 (0.016)        |
| 17 | 0.971 (0.012)        | 0.967 (0.016)        | 0.963 (0.014)        |
| 18 | 0.973 (0.014)        | 0.971 (0.011)        | 0.966 (0.016)        |
| 19 | <b>0.979 (0.008)</b> | 0.970 (0.014)        | <b>0.968 (0.013)</b> |
| 20 | 0.965 (0.012)        | 0.960 (0.014)        | 0.930 (0.023)        |
| 21 | <b>0.900 (0.033)</b> | <b>0.892 (0.034)</b> | <b>0.482 (0.039)</b> |
| 22 | 0.949 (0.021)        | 0.944 (0.020)        | 0.920 (0.026)        |
| 23 | 0.978 (0.007)        | 0.969 (0.013)        | 0.971 (0.005)        |
| 24 | 0.944 (0.111)        | 0.945 (0.083)        | 0.927 (0.118)        |
| 25 | 0.980 (0.009)        | 0.978 (0.010)        | 0.975 (0.009)        |
| 26 | <b>0.982 (0.009)</b> | <b>0.979 (0.008)</b> | <b>0.980 (0.006)</b> |
| 27 | 0.976 (0.012)        | 0.970 (0.023)        | 0.968 (0.023)        |
| 28 | 0.947 (0.020)        | 0.937 (0.029)        | 0.929 (0.022)        |
| 29 | 0.967 (0.013)        | 0.964 (0.023)        | 0.969 (0.007)        |
| 30 | 0.972 (0.012)        | 0.966 (0.009)        | 0.958 (0.016)        |
| 31 | 0.975 (0.015)        | 0.975 (0.013)        | 0.975 (0.009)        |
| 32 | 0.977 (0.013)        | 0.978 (0.008)        | 0.977 (0.012)        |
| 33 | 0.980 (0.009)        | 0.976 (0.016)        | 0.978 (0.010)        |
| 34 | 0.977 (0.010)        | 0.970 (0.015)        | 0.971 (0.016)        |
| 35 | <b>0.788 (0.053)</b> | <b>0.794 (0.062)</b> | <b>0.732 (0.061)</b> |
| 36 | <b>0.794 (0.078)</b> | <b>0.788 (0.085)</b> | <b>0.760 (0.062)</b> |
| 37 | <b>0.608 (0.122)</b> | <b>0.656 (0.122)</b> | <b>0.599 (0.119)</b> |
| 38 | 0.793 (0.095)        | 0.779 (0.096)        | 0.737 (0.066)        |

\*The values inside curved brackets represent the standard deviation.

decoding at the high-level and predefined torque selection at the mid-level. However, active assistance for SD and was not included, and validation was limited to able-bodied subjects. In [12], hybrid control assisted the knee joint: applying active torque during stance and zero-torque during swing. Assistance types varied with LM: sinusoidal closed-loop control for SA and open-loop damping for LGW and SD. Yet, the lack of swing/phase support and suboptimal stance/phase were noted. Conversely, study [13] applied predefined torque patterns across the gait cycle depending on the decoded LM, but reported high response delays (ranging from 300 to 1000 ms after the critical instant), potentially causing user discomfort.

We believe that support during the swing phase is crucial, as this is when the ankle executes rapid movements between plantar flexion and dorsiflexion during tasks such as SA and LGW. According to [42], stroke patients are characterized by reduced dorsiflexion and plantarflexion movements. Therefore, not supporting these movements during the swing phase of tasks such as SA and LGW may not be the most appropriate strategy to meet the needs of stroke patients.

Our study advances studies [12], [13] by timely adapting the assistance of an active ankle orthosis according to the predicted LM. Assistance is provided during the entire gait cycle, and it is adapted before the user reaches the upcoming LM (between the mid- and terminal swing of the gait cycle preceding the upcoming LM). Supplementary videos present the control adaptation across the six transitions: St-LGW, LGW-St, LGW-SD, SD-LGW, LGW-SA, and SA-LGW.

## VII. CONCLUSION

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 four LMs (St, LGW, SD, and SA) and transitions between them; and (ii) to develop an LM-driven position control strategy that timely adapts the assistance of an active ankle orthosis according to the LM decoded.

This study 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 able-bodied and stroke participants, presenting a low computational load. In addition, the tool proved to be robust to different gait speeds (from 1.0 to 1.6 km/h) and different scenarios. These conclusions highlight the suitability of the developed LM decoding tool and control strategy in the timely adaptation of the SmartOs system to assist users with daily walking tasks.

## APPENDIX

See Table A1.

## REFERENCES

- [1] L. Moreira, J. Figueiredo, J. Cerqueira, and C. P. Santos, "A review on locomotion mode recognition and prediction when using active orthoses and exoskeletons," *Sensors*, vol. 22, no. 19, p. 7109, Sep. 2022, doi: [10.3390/s22197109](https://doi.org/10.3390/s22197109).
- [2] F. Labarrière et al., "Machine learning approaches for activity recognition and/or activity prediction in locomotion assistive devices—A systematic review," *Sensors*, vol. 20, no. 21, pp. 1–30, 2020.
- [3] C. Gong, D. Xu, Z. Zhou, N. Vitiello, and Q. Wang, "Real-time on-board recognition of locomotion modes for an active pelvis orthosis," in *Proc. IEEE-RAS 18th Int. Conf. Humanoid Robots (Humanoids)*, 2018, pp. 346–350, doi: [10.1109/HUMANOIDS.2018.8625044](https://doi.org/10.1109/HUMANOIDS.2018.8625044).
- [4] Z. Zhou, X. Liu, Y. Jiang, J. Mai, and Q. Wang, "Real-time onboard SVM-based human locomotion recognition for a bionic knee exoskeleton on different terrains," in *Proc. Wearable Robot. Assoc. Conf. (WearRAcon)*, 2019, pp. 34–39, doi: [10.1109/WEARRACON.2019.8719399](https://doi.org/10.1109/WEARRACON.2019.8719399).
- [5] Y. Qian et al., "Predictive locomotion mode recognition and accurate gait phase estimation for hip exoskeleton on various terrains," *IEEE Robot. Autom. Lett.*, vol. 7, no. 3, pp. 6439–6446, Jul. 2022, doi: [10.1109/LRA.2022.3173426](https://doi.org/10.1109/LRA.2022.3173426).
- [6] Y. Qian et al., "Terrain-adaptive exoskeleton control with predictive gait mode recognition: A pilot study during level walking and stair ascent," *IEEE Trans. Med. Robot. Bionics*, vol. 6, no. 1, pp. 281–291, Feb. 2024, doi: [10.1109/TMRB.2024.3349624](https://doi.org/10.1109/TMRB.2024.3349624).
- [7] S. Jing, H.-Y. Huang, R. Vaidyanathan, and D. Farina, "Accurate and robust locomotion mode recognition using high-density EMG recordings from a single muscle group," in *Proc. 44th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, 2022, pp. 686–689, doi: [10.1109/EMBC48229.2022.9871155](https://doi.org/10.1109/EMBC48229.2022.9871155).

- [8] W. Wang, L. Zhang, J. Liu, B. Zhang, and Q. Huang, "A real-time walking pattern recognition method for soft knee power assist wear," *Int. J. Adv. Robot. Syst.*, vol. 17, no. 3, May 2020, Art. no. 1729881420925291, doi: [10.1177/1729881420925291](https://doi.org/10.1177/1729881420925291).
- [9] C. Gong, D. Xu, Z. Zhou, N. Vitiello, and Q. Wang, "BPNN-based real-time recognition of locomotion modes for an active pelvis orthosis with different assistive strategies," *Int. J. Humanoid Robot.*, vol. 17, Feb. 2020, Art. no. 2050004, doi: [10.1142/S0219843620500048](https://doi.org/10.1142/S0219843620500048).
- [10] P. Zhang, J. Zhang, and A. Elsabbagh, "Lower limb motion intention recognition based on sEMG fusion features," *IEEE Sensors J.*, vol. 22, no. 7, pp. 7005–7014, Apr. 2022, doi: [10.1109/JSEN.2022.3146446](https://doi.org/10.1109/JSEN.2022.3146446).
- [11] J. Liu, X. Zhou, B. He, P. Li, C. Wang, and X. Wu, "A novel method for detecting misclassifications of the locomotion mode in lower-limb exoskeleton robot control," *IEEE Robot. Autom. Lett.*, vol. 7, no. 3, pp. 7779–7785, Jul. 2022, doi: [10.1109/LRA.2022.3185380](https://doi.org/10.1109/LRA.2022.3185380).
- [12] X. Liu and Q. Wang, "Real-time locomotion mode recognition and assistive torque control for unilateral knee exoskeleton on different terrains," *IEEE/ASME Trans. Mechatronics*, vol. 25, no. 6, pp. 2722–2732, Dec. 2020, doi: [10.1109/TMECH.2020.2990668](https://doi.org/10.1109/TMECH.2020.2990668).
- [13] G. Du, J. Zeng, C. Gong, and E. Zheng, "Locomotion mode recognition with inertial signals for hip joint exoskeleton," *Appl. Bionics Biomech.*, vol. 2021, pp. 1–11, May 2021, doi: [10.1155/2021/6673018](https://doi.org/10.1155/2021/6673018).
- [14] L. Zhu et al., "A novel motion intention recognition approach for soft exoskeleton via IMU," *Electronics*, vol. 9, no. 12, p. 2176, Dec. 2020, doi: [10.3390/electronics9122176](https://doi.org/10.3390/electronics9122176).
- [15] Z. Ding, C. Yang, Z. Wang, X. Yin, and F. Jiang, "Online adaptive prediction of human motion intention based on sEMG," *Sensors*, vol. 21, no. 8, p. 2882, Apr. 2021, doi: [10.3390/s21082882](https://doi.org/10.3390/s21082882).
- [16] J.-J. Lin, C.-K. Hsu, W.-L. Hsu, T.-C. Tsao, F.-C. Wang, and J.-Y. Yen, "Machine learning for human motion intention detection," *Sensors*, vol. 23, no. 16, p. 7203, Aug. 2023, doi: [10.3390/s23167203](https://doi.org/10.3390/s23167203).
- [17] H. Huang, F. Zhang, L. J. Hargrove, Z. Dou, D. R. Rogers, and K. B. Englehart, "Continuous locomotion-mode identification for prosthetic legs based on neuromuscular-mechanical fusion," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 10, pp. 2867–2875, Oct. 2011, doi: [10.1109/TBME.2011.2161671](https://doi.org/10.1109/TBME.2011.2161671).
- [18] P. N. Fernandes, S. Carvalho, J. Figueiredo, J. C. Moreno, and C. P. Santos, "Feedback-error learning for gait rehabilitation using a powered knee orthosis: First advances," in *Proc. IEEE 6th Portuguese Meeting Bioeng. (ENBENG)*, 2019, pp. 1–4, doi: [10.1109/ENBENG.2019.8692502](https://doi.org/10.1109/ENBENG.2019.8692502).
- [19] C. B. Beamman, C. L. Peterson, R. R. Neptune, and S. A. Kautz, "Differences in self-selected and fastest-comfortable walking in post-stroke hemiparetic persons," *Gait Posture*, vol. 31, no. 3, pp. 311–316, 2010, doi: [10.1016/j.gaitpost.2009.11.011](https://doi.org/10.1016/j.gaitpost.2009.11.011).
- [20] M. R. Tucker et al., "Control strategies for active lower extremity prosthetics and orthotics: A review," *J. Neuroeng. Rehabil.*, vol. 12, no. 1, p. 1, 2015, doi: [10.1186/1743-0003-12-1](https://doi.org/10.1186/1743-0003-12-1).
- [21] J. Figueiredo, S. Carvalho, J. P. Vilas-Boas, L. M. Gonçalves, J. C. Moreno, and C. P. Santos, "Wearable inertial sensor system towards daily human kinematic gait analysis: Benchmarking analysis to MVN BIOMECH," *Sensors*, vol. 20, no. 8, p. 2185, 2020, doi: [10.3390/s20082185](https://doi.org/10.3390/s20082185).
- [22] "TRIGNO <sup>®</sup> wireless system SDK user's guide," Delsys Incorporated. 2019. [Online]. Available: <https://www.delsys.com/downloads/USERSGUIDE/trigno/sdk.pdf>
- [23] M. Bortole et al., "The H2 robotic exoskeleton for gait rehabilitation after stroke: Early findings from a clinical study," *J. Neuroeng. Rehabil.*, vol. 12, no. 1, p. 54, Dec. 2015, doi: [10.1186/s12984-015-0048-y](https://doi.org/10.1186/s12984-015-0048-y).
- [24] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, and G. Rau, "Development of recommendations for SEMG sensors and sensor placement procedures," *J. Electromyogr. Kinesiol.*, vol. 10, pp. 361–374, Oct. 2000, doi: [10.1007/s10750-015-2551-3](https://doi.org/10.1007/s10750-015-2551-3).
- [25] L. Moreira, J. Figueiredo, P. Fonseca, J. P. Vilas-Boas, and C. P. Santos, "Lower limb kinematic, kinetic, and EMG data from young healthy humans during walking at controlled speeds," *Sci. Data*, vol. 8, no. 1, p. 103, Apr. 2021, doi: [10.1038/s41597-021-00881-3](https://doi.org/10.1038/s41597-021-00881-3).
- [26] M. M. Ardestani, C. Ferrigno, M. Moazen, and M. A. Wimmer, "From normal to fast walking: Impact of cadence and stride length on lower extremity joint moments," *Gait Posture*, vol. 46, pp. 118–125, May 2016, doi: [10.1016/j.gaitpost.2016.02.005](https://doi.org/10.1016/j.gaitpost.2016.02.005).
- [27] "Stairs" exercise with left hemiplegia due to CVA." 2023. [Online]. Available: <https://www.dpemed.com/post/stairs-exercise-with-left-hemiplegia-due-to-cva>
- [28] D. R. Martins, S. M. Cerqueira, and C. P. Santos, "Seeking optimal and explainable deep learning models for inertial-based posture recognition," *TechRxiv*, Preprint, 2024, doi: [10.36227/techrxiv.170492244.42056676/v1](https://doi.org/10.36227/techrxiv.170492244.42056676/v1).
- [29] S. Tortora, S. Ghidoni, C. Chisari, S. Micera, and F. Artoni, "Deep learning-based BCI for gait decoding from EEG with LSTM recurrent neural network," *J. Neural Eng.*, vol. 17, no. 4, Jul. 2020, Art. no. 46011, doi: [10.1088/1741-2552/ab9842](https://doi.org/10.1088/1741-2552/ab9842).
- [30] G. Khodabandelou, H. Moon, Y. Amirat, and S. Mohammed, "A fuzzy convolutional attention-based GRU network for human activity recognition," *Eng. Appl. Artif. Intell.*, vol. 118, Feb. 2023, Art. no. 105702, doi: [10.1016/j.engappai.2022.105702](https://doi.org/10.1016/j.engappai.2022.105702).
- [31] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2017, *arXiv:1412.6980*.
- [32] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollar, "Focal loss for dense object detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 42, no. 2, pp. 318–327, Feb. 2020, doi: [10.1109/TPAMI.2018.2858826](https://doi.org/10.1109/TPAMI.2018.2858826).
- [33] B. K. Iwana and S. Uchida, "An empirical survey of data augmentation for time series classification with neural networks," *PLoS ONE*, vol. 16, no. 7, Jul. 2021, Art. no. e0254841, doi: [10.1371/journal.pone.0254841](https://doi.org/10.1371/journal.pone.0254841).
- [34] T. T. Um et al., "Data augmentation of wearable sensor data for parkinson's disease monitoring using convolutional neural networks," in *Proc. 19th ACM Int. Conf. Multimodal Interact.*, 2017, pp. 216–220, doi: [10.1145/3136755.3136817](https://doi.org/10.1145/3136755.3136817).
- [35] P. Félix, J. Figueiredo, C. P. Santos, and J. C. Moreno, "Electronic design and validation of powered knee orthosis system embedded with wearable sensors," in *Proc. 17th Int. Conf. Auton. Robot Syst. Compet.*, 2017, pp. 110–115.
- [36] J. S. C. Figueiredo, *Smart Wearable Orthosis to Assist Impaired Human Walking*, Univ. Minho, Braga, Portugal, 2019.
- [37] J. Figueiredo, P. N. Fernandes, J. C. Moreno, and C. P. Santos, "Feedback-error learning for time-effective gait trajectory tracking in wearable exoskeletons," *Anat. Rec.*, vol. 306, no. 4, pp. 728–740, Apr. 2023, doi: [10.1002/ar.25031](https://doi.org/10.1002/ar.25031).
- [38] C. Yoon-Hee, "Lower limb muscle activities and gain in balancing ability following two types of stair gait intervention in adult post-chronic stroke patients: A preliminary, randomized-controlled study," *Turkish J. Phys. Med. Rehabil.*, vol. 66, no. 1, pp. 17–23, Mar. 2020, doi: [10.5606/tftrd.2020.3335](https://doi.org/10.5606/tftrd.2020.3335).
- [39] S. Li, G. E. Francisco, and P. Zhou, "Post-stroke Hemiplegic gait: New perspective and insights," *Front. Physiol.*, vol. 9, pp. 1–8, Aug. 2018, doi: [10.3389/fphys.2018.01021](https://doi.org/10.3389/fphys.2018.01021).
- [40] P. Heinemann and M. Kasperski, "Damping induced by walking and running," *Procedia Eng.*, vol. 199, pp. 2826–2831, Jan. 2017, doi: [10.1016/j.proeng.2017.09.537](https://doi.org/10.1016/j.proeng.2017.09.537).
- [41] D. A. Winter, *Biomechanics and Motor Control of Human Movement*. Hoboken, NJ, USA: Wiley, 2009.
- [42] L. Bensoussan, S. Mesure, J.-M. Viton, and A. Delarque, "Kinematic and kinetic asymmetries in hemiplegic patients' gait initiation patterns," *J. Rehabil. Med.*, vol. 38, no. 5, pp. 287–294, Sep. 2006, doi: [10.1080/16501970600694859](https://doi.org/10.1080/16501970600694859).