



Locomotion mode prediction in real-life walking with and without ankle–foot exoskeleton assistance

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Abstract

Exoskeletons can assist human locomotion in real-life scenarios, but existing tools for decoding locomotion modes (LMs) focus on recognition rather than prediction, which can lead to delayed assistance. This study proposes a long short-term memory (LSTM) neural network to predict five LMs (level-walking, ramp ascent/descent, stair ascent/descent) with greater lead time compared to state-of-the-art methods. We examined the optimal sequence length (SL) for LSTM-based LM prediction, using data from inertial sensors placed on the lower limbs and the lower back, along with a waist-mounted infrared laser. Ten subjects walked in real-life scenarios, both with and without an ankle–foot exoskeleton. Results show that a 1-s SL provides the most advanced and accurate LM prediction, outperforming SLs of 0.6, 0.8, and 1.2 s. The proposed LSTM model achieved an accuracy of $98 \pm 0.31\%$, predicting LMs 0.66 s in advance (for an average stride time of 1.98 ± 0.83 s). Level-walking presented more misclassifications, and the model primarily relied on inertial data over laser input. Overall, these findings demonstrate the LSTM's strong predictive capability for both assisted and non-assisted walking and independent of which limb executes the transition, supporting its applicability for exoskeleton-assisted locomotion.

Keywords Deep learning · Exoskeleton · Locomotion mode prediction · LSTM neural network · Motion intention decoding · Gait rehabilitation

1 Introduction

Human gait exhibits distinct biomechanical characteristics depending on the type of terrain [1]. Consequently, each terrain type requires a specific locomotion mode (LM). However,

patients with lower limb motor disabilities face challenges in performing common LMs encountered in daily life, such as level-ground walking (LW), stair descent (SD), stair ascent (SA), ramp descent (RD), and ramp ascent (RA) [2]. Advancements in active robotic assistive devices, particularly lower limb exoskeletons and prostheses, are opening new possibilities for gait assistance in daily-life locomotion [3–5]. For these robotic devices to be effective, they must combine two key abilities: (i) accurately and timely decoding LMs [4]; (ii) automatically adjusting the devices' control parameters to provide adaptable gait assistance based on the decoded LM [6, 7]. These abilities are necessary for ensuring safe transitions across terrains and seamless human–robot interaction [4].

Currently, commercially available active lower limb prosthetics and exoskeletons use remote-controlled button presses, tapping of the foot, or other unnatural body movements to indicate a change in the LM to the device [7, 8]. These non-automatic methods are unnatural, time-consuming, and cognitively demanding, limiting the effectiveness of assistive devices in daily-life locomotion tasks.

Promising automatic LM decoding tools have been achieved using different types of wearable sensors, such as

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electromyography (EMG) [3, 9–12], Inertial Measurement Units (IMUs) [13–15], laser [16], device-embedded sensors (e.g., pressure, load cells or encoders), and sensor fusion techniques [16–21]. EMG signals have been considered due to their anticipatory nature and potential for decoding LMs in advance. However, EMG use has several drawbacks, such as (i) the need for expertise in sensor placement, (ii) susceptibility to cross-talk interferences, and (iii) poor reliability in subjects with motor impairments [7, 22]. More recent works [13, 14] have studied the exclusive use of kinematic data from IMUs for LM decoding. These studies reported high performance in LM recognition (i.e., detecting the LM once the user is already performing it), but tools for LM prediction (i.e., detecting the LM before the user transitions into it) still require higher accuracy. Further studies [16, 17, 21, 23] have sought to improve the time-effectiveness of LM prediction by including context-awareness information from RGB [21, 24–26], depth cameras [21, 27, 28], and lasers [16]. Given the high computational demands of processing image and video data, laser sensors are a more feasible solution for wearable assistive devices. Promising results have been achieved when laser sensors are used alone [16] and fused with IMUs and EMGs [17].

A large range of classification methods have been used to address the LM decoding problem, including heuristic rule-based classifiers [16, 29, 30], machine learning classifiers (e.g., support vector machine (SVM), linear discriminant analysis (LDA), k-nearest neighbors (KNN), random forest (RA)) [3, 6, 13, 31, 32], and combinations of them [17]. Deep neural networks are increasingly being used, as they eliminate the need for complex feature extraction methods while simultaneously achieving high performance as increases the number of classified LMs [19, 33].

Despite these advances, several challenges remain in the state-of-the-art of LM decoding. First, most studies on exoskeleton-based assisted gait focused on LM recognition rather than LM prediction [34–36]. This delayed detection of LMs can result in undesirable operation of the assistive device and a lag in transitioning between LMs. Second, the existing LM prediction tools, both with and without exoskeletons, do not predict LMs far enough in advance to trigger robotic assistance in a timely manner for daily locomotion [18, 37–39]. While they do detect the LM before it occurs, the lead time is insufficient to effectively control assistive devices. Third, there remains a lack of versatile prediction tools that can be applied across different assistive devices, which would eliminate the need for time-consuming, device-specific tuning [18, 19, 40, 41]. Finally, the majority of LM decoding tools are limb-dependent, i.e., they require a pre-defined limb to perform the LM transition [21, 41], which is unnatural and cognitively demanding for daily use.

This work addresses these challenges by proposing a deep learning LM prediction tool that decodes five common

real-life LMs (indoor and outdoor LW, SD, SA, RA, and RD) under both assisted and non-assisted gait conditions using an ankle–foot exoskeleton. The tool uses a long short-term memory (LSTM) neural network fed by the lower back and lower limb kinematic data, and a single beam laser data, both tracked by wearable sensors. The best sequence length for LM prediction was studied. This work introduces a novel LM prediction tool with the following contributions: (i) the ability to predict five LMs with longer lead time compared to literature studies [18, 37–39], which, furthermore, were not capable to predict all five LMs; (ii) reliability in both assisted and non-assisted gait conditions, suggesting its potential for use across different devices without requiring device-specific tuning; and, (iii) independence from the limb that performing the LM transitions. Moreover, this study explores two key hypotheses. First, we hypothesize that integrating anticipatory environmental data from a single laser signal [16] will improve prediction accuracy compared to using kinematic data alone, as proposed in our previous work [13]. Second, we aim to leverage the LSTM's inherent ability to retain time-history information—mirroring the human ability to make decisions based on past experiences—to enable more advanced predictions. Overall, the methods and findings from this study contribute to earlier detection of LMs, thereby improving the performance of assistive devices in real-life gait assistance.

2 Related work

Several approaches have been proposed for recognizing or predicting LMs in both non-assisted and assisted conditions. Table 1 presents the works related to our study. For non-assisted conditions, study [42] employed an LSTM to decode six LMs from inertial data, achieving an accuracy of 87.4%, while Gregory et al. [12] reached an accuracy of 77.2% using EMG data. Zhao et al. [43] reported more accurate classification by fusing EMG with ankle motion data. Nevertheless, these studies [12, 42, 43] focused on recognizing current LMs rather than predicting upcoming ones. In contrast, study [38] proposed a prediction tool that relies on sequential classification models. However, this approach propagates misclassifications through the classification stages, leading to lower performance.

In assisted conditions, the development of LM decoding tools is more advanced for locomotion assisted by prosthesis-assisted locomotion compared to exoskeletons [7]. As summarized in Table 1, recent studies [20, 32, 44] have proposed accurate tools for decoding six [20, 44] and five [32] LMs using sensors embedded in prostheses. These studies achieved high accuracy, namely 98.8% [44], 99% [32], and 92.7% [20]. Nonetheless, the decoding tools proposed for prostheses-driven assistance share several limitations: (i) they do not

Table 1 Related work in LM decoding for non-assisted and assisted walking: Level walking (LW), ramp descent (RD), ramp ascent (RA), stair ascent (SA), stair descent (SD), and standing (ST). R and P mean recognition and prediction, respectively

Study	R/P	Locomotion Tasks	Sensors (location)	Classifier	Performance (accuracy)	Participants
Gregory et al. [12]	R	Foot dorsiflexion and plantarflexion, foot eversion and inversion	EMG (Tibialis A., Gastrocnemius, Rectus F., Vastus M., Biceps F. and semitendinosus)	LDA	77.2%	6 healthy subjects
Sherratt et al. [42]	R	LW, SA, SD, RA, RD, Stop	5 IMUs (right/left ankles, right/left hips, chest)	LSTM	87.4% for validation and 84.7% for test	22 healthy subjects
Zhao et al. [43]	R	Sit, Standing, Stand up/down, LW, Stretch the knee, Dorsiflexion, Plantarflexion, Squat, Jump	EMG (Rectus F., Biceps F., Semitendinosus, Tibialis A., Gastrocnemius) and ankle acceleration	SVM	93.69%	Not specified
Papapicco et al. [38]	P	LW, SA, SD	2 IMUs (thigh)	SVM	Between 75 and 85%	10 healthy subjects
Spanias et al. [44]	R	LW, SA, SD, RA, RD, ST	Prosthesis Sensors (position sensor and torque sensor at the knee and ankle)	LDA	98.8%	6 unilateral lower limb amputees
Zheng et al. [20]	R	LW, SA, SD, RA, RD, ST	Prosthesis Sensors (2 IMUs, angle sensor, force sensor with strain gauges)	QDA and SVM	92.7%	6 transtibial amputees
Young et al. [32]	R	LW, SA, SD, RA, RD	Prosthesis Sensors (potentiometer and encoder at the knee and ankle, an axial load cell, 1 IMU on the shank)	LDA	99%	8 subjects with unilateral trans-femoral or knee disarticulation amputations
Wang et al. [19]	R	Sitting Down, Standing up, LW, SA, SD	Exoskeleton Sensors (Encoder at the hips, knees, and ankles)	LSTM	Between 96.32% and 99.52%	22 healthy subjects
Beil et al. [34]	R	LW, walking backward, turn left, turn right, sidesteps right, sidesteps left, SA, SD, lift an object, drop an object, stand up and sit down	Exoskeleton Sensors (7 3D-force sensors and 3 IMUs in thigh, shank, and foot)	Hidden Markov Models	92.8%	10 healthy subjects
Wang et al. [45]	R	LW, SA, SD, RA, RD, standing, sitting, and squatting Transitions (stand to sit, sit to stand, stand to squat, and squat to stand)	Exoskeleton Sensors (6-axis force sensors and 4 IMUs in thighs and shanks)	Genetic Algorithm-CNN	Between 92.96% and 98%	6 healthy subjects
Gong et al. [35]	R	ST, LW, SA, SD, RA, RD	Exoskeleton sensors (1 IMU in thigh)	MFNN	Between 97.6% and 98.4%	3 healthy subjects
Wang et al. [46]	R	LW, SA, SD and Transitions (LW → SA, SA → LW, LW → SD, SD → LW)	Exoskeleton sensors (2 IMUs in thigh and shank)	FSM	Between 98.1% and 98.3%	18 healthy subjects

Table 1 (continued)

Study	R/P	Locomotion Tasks	Sensors (location)	Classifier	Performance (accuracy)	Participants
Du et al. [47]	R	ST, LW, SA, SD, and Transitions (LW → ST, ST → LW)	Exoskeleton sensors (2 IMUs in thigh)	Fuzzy-logic method	Between 89% and 91.9%	3 healthy subjects
Liu et al. [37]	Both	LW, SA, SD, and Transitions (LW → SA, SA → LW, LW → SD, SD → LW)	Exoskeleton sensors (2 IMUs in thigh and shank)	SVM	Between 97.6% and 98.3%	5 healthy subjects; 1 stroke
Zhou et al. [18]	Both	LW, SA, SD and Transitions (LW → SA, SA → LW, LW → SD, SD → LW)	Exoskeleton sensors (2 IMUs at the thigh and shank)	SVM	Between 93% and 96.2%	3 (healthy)
Xunju et al. [39]	Both	LW, SA, SD, RA, RD and Transitions LW ↔ SA, LW ↔ SD, LW ↔ RA, and LW ↔ RD	Exoskeleton sensors (plantar pressure, and 8 IMUs in back, thighs, shanks, and feet)	CNN-BiLSTM	Between 87.04% and 99.58%	6 healthy subjects

predict the LMs; (ii) they are limited to a specific prosthetic device; and (iii) they require a specific limb to perform the LM transitions.

Similar to our work, studies [18, 19, 34, 35, 37, 39, 45–47] developed LM decoding tools for exoskeleton-assisted walking. Studies [34] and [19] decoded five LMs with 92.8% and 95% accuracy based on Hidden Markov Models and an LSTM, respectively. Study [45] achieved 97.91% accuracy using a convolution neural network (CNN). These studies [19, 34, 39, 45] used multiple sensors, including force sensors and IMUs, distributed across the lower limb joints of the exoskeleton. Other studies have successfully recognized LMs using less intrusive sensor setups, placing IMUs on thigh and shank [18, 37, 46], or exclusively on thigh [35, 47]. Although highly accurate LM decoding tools have been proposed, studies [19, 34, 35, 45–47] focus solely on LM recognition, detecting the LM only after the user has already begun the movement. This delay does not allow sufficient time to adjust the exoskeleton's control parameters in response, making these tools less suitable for exoskeleton-assisted walking [6, 7]. In contrast, Zhou et al. [18] and Liu et al. [37] developed SVM models that predicted three LMs with over 93% accuracy, using data from three and five healthy subjects wearing a knee exoskeleton, respectively. However, existing LM prediction tools for exoskeletons [18, 37, 39] have reported delayed decoding for certain LMs, as these were predicted during the stance phase of the new LM. This indicates that current tools have not been fully effective in predicting all LMs in advance.

3 Methods

We developed a LM prediction tool based on an LSTM model, implemented in Matlab® (2019a, The Mathworks, MA, USA), using sensor data acquired from experimental procedures conducted in real-life scenarios. All collected data were organized into a dataset containing sensor data and anthropometric measurements for each participant. The dataset was segmented into specific sequence lengths (SLs) for LSTM training. Next, a cross-validation procedure was employed to assess the LSTM model's generalization ability and identify the most reliable SL. Finally, the best model was tested on unseen data. Figure 1 illustrates an overview of the methodology, which is described in detail in the following sub-sections.

3.1 Dataset acquisition

3.1.1 Participants

Able-bodied participants were recruited according to the following inclusion criteria: (i) healthy locomotion; (ii) more than 18 years old; (iii) body mass ranging from 45 to 90 kg; and (iv) body height ranging from 1.50 to 1.90 m. We

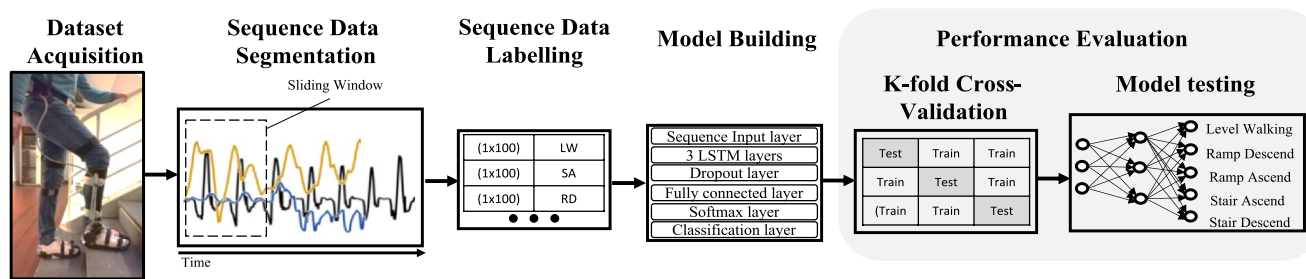


Fig. 1 LM classification procedure using the LSTM neural network. Dataset Acquisition provides sensor data that are segmented into sequences in Sequence Data Segmentation and labelled in Sequence Data Labelling. The labelled sequences are processed in Model Building to create the LSTM for LM classification, which is validated in Performance Evaluation

selected 10 able-bodied subjects (7 males and 3 females) for the data acquisition procedure. The participants' mean age was 24.7 ± 1.77 years old, with a mean height of 172.2 ± 10.1 cm and a mean body mass of 70.7 ± 11.97 kg. All participants provided written and informed consent according to the ethical conduct defined by the University of Minho Ethics Committee (CEICVS 006/2020), and to publish identifiable images.

3.1.2 Equipment

For kinematic data collection, we used Mtw Awinda® (Xsens Technologies B.V., The Netherlands) given its high reliability (angular resolution of 0.05 deg [48]) for ambulatory tracking of human kinematics through high-precision, magnetically immune, miniaturized IMUs [49]. The 3D kinematic data of the lower limbs were acquired using the Mtw Awinda's lower limb setup (7 IMUs, Fig. 2-yellow circle). Moreover, we used a team-developed wearable infrared laser system (TFMini Lidar®) [16] to acquire environmental context data. This laser system (Fig. 2-blue hexagon) was

placed on the user's waist using a 3D-printed holder to measure the distance between the user and the terrain ahead, in both indoor and outdoor conditions. The 3D-printed holder included a mechanism to regulate the laser's pointing angle, which was set at 45° relative to the user's abdomen for all participants. This orientation aims to prevent undesired reflection from the user's legs (below 45°), walls, or moving people (above 45°), as described in [16]. Table 4 presents the main specifications of the sensor systems.

In the assisted walking experiments, the participants were equipped with an ankle-foot exoskeleton (H2 exoskeleton, Technaid, Spain) (Fig. 2-black box). The exoskeleton assists in the sagittal plane for gait speed ranging from 0.5 to 1.6 km/h through an electrical actuator (flat brushless DC motor EC60-100 W, Maxon) coupled with a gearbox (CSD20-160-2A gear, Harmonic Drive), providing a nominal torque of 35 Nm. It endows a precision potentiometer for measuring angular position and four strain gauges (configured in a full Wheatstone bridge) to track the user-exoskeleton interaction torque. During assisted walking, the exoskeleton was controlled by a zero-impedance control strategy



Fig. 2 Equipment used in the data acquisition procedures

that allows free movement of the users' joints according to their motion intention by minimizing the mechanical impedance (passive resistance) from the actuator. More details are described in [50].

A central controlling unit (CCU), the Raspberry Pi 4 (Raspberry Pi Foundation, UK), running on Ubuntu Mate OS, manages the exoskeleton control, synchronizes data acquisition, and logs data from the exoskeleton's embedded sensors and the laser system. The CCU also handles the synchronization with MT manager software (MTw Awinda®), running on an external Windows computer board, using the TTL sync method. A user-friendly mobile application (Android) communicates via Bluetooth with CCU, enabling intuitive setup of the exoskeleton assistance, start/stop data acquisition, and marking of terrain transitions. The power supply system includes a lithium iron phosphate battery (LifePO4, 22.4 VDC, 12 Ah) to supply the CCU, exoskeleton, and laser system.

3.1.3 Experimental protocol

We started the experiments by measuring the participants' anthropometric data, which included: i) leg and foot length, and body height using a measuring tape, and ii) the body mass using a balance. Subsequently, seven IMUs were placed on the outer side of the thighs and shanks, on top of the feet, and one on the lower back. After this, we instrumented the participants with the laser sensor attached to

their waist, and a backpack containing the CCU, battery, and cables to connect the CCU to the laser sensor and the exoskeleton. Next, the N-pose + Walk calibration procedure was conducted for the MTw Awinda®, with the participants standing in N-pose for 3 s, followed by walking 5 m forward and backward in a straight line (according to the manufacturer's instructions). Then, the participants stood still for 5 s to calibrate the laser system. The laser calibration automatically occurred during the first 5 s of each trial, where the mean value of the distance signal (between the ground and the sensor) was computed and removed to set the baseline to zero, as detailed in [16].

The experimental procedure included two protocols: Protocol I for non-assisted walking and Protocol II for assisted walking by the ankle-foot exoskeleton. In both protocols, participants performed 5 continuous trials at a self-selected gait speed, in a real-life circuit that features different indoor and outdoor terrains. The circuit, depicted in Fig. 3, includes five LMs, namely: LW, RD, RA, SA, and SD. Each participant performed the following sequence of terrains (LM indicated under brackets), illustrated in Fig. 3: (i) standing for 5 s; (ii) walking forward on level ground for 10 m (LW); (iii) descend a 10-m length ramp (RD); (iv) walking forward on level ground for 10 m (LW); (v) ascend a 10-m length ramp (RA); (vi) walking forward on level ground for 13 m (LW); (vii) ascend an 8 step staircase (SA); (viii) walking forward on level ground for 2 m; (ix) descend an 8 step staircase (SD); (x) walking forward on level ground for 3 m (LW);

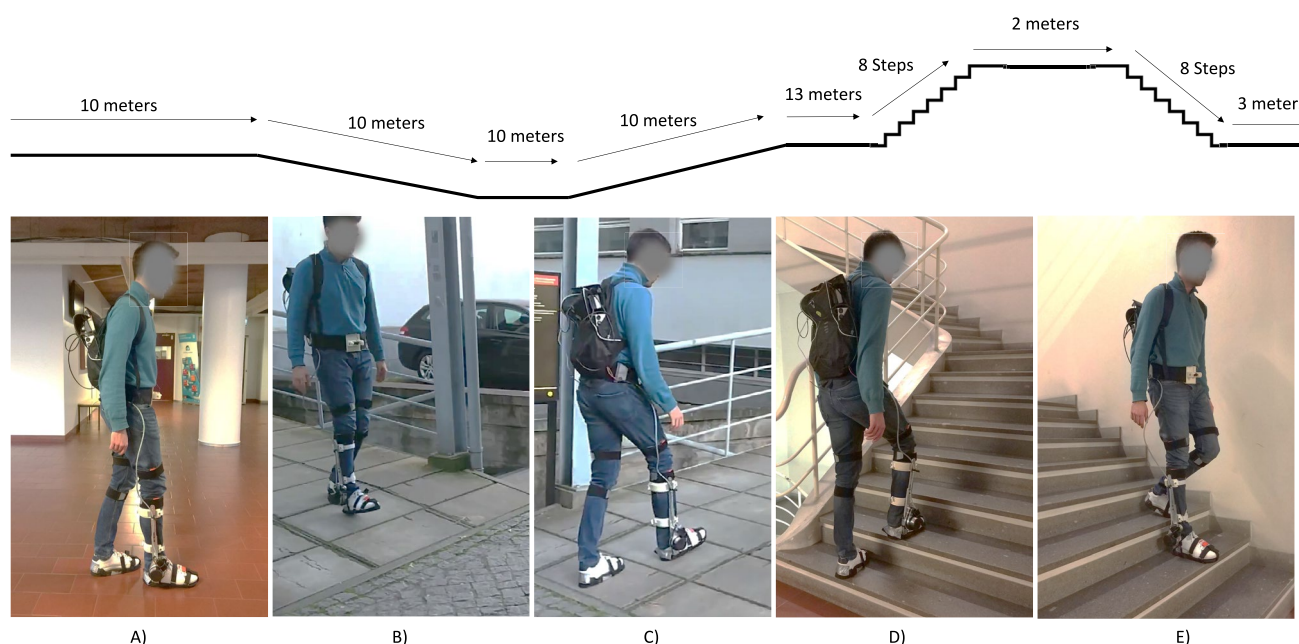


Fig. 3 Top view provides an illustration of experimental procedure used in protocols I and II. Bottom view shows images from the experimental procedure during protocol II. A) Level walking (LW); B) Ramp Descent (RD); C) Ramp Ascent (RA); D) Stair Ascent (SA); E) Stair Descent (SD)

and, (xi) stop. This protocol builds upon previous teamwork [13] and existing literature (in-laboratory terrains) [18, 32, 51] by allowing the participants to walk continuously across different terrains rather than performing isolated trials per terrain. The indoor staircase (Fig. 3 D) and E)) has 8 steps each with 17 cm of height, 31 cm of depth, and 110 cm in width. The outdoor ramp (Fig. 3 B) and C)) was 10 m with a 10° inclination. An experimenter walked alongside the subjects marking the LM transition moments using a digital button on a mobile application [13]. The CCU synchronously recorded these marked LM transition moments along with the sensor data.

3.1.4 Data collection

The collected data shows a mean gait speed of 0.99 ± 0.09 m/s for Protocol I and 0.36 ± 0.11 m/s for Protocol II. In Protocol I, a total of 64 different sensor signals were recorded, including 3-axis acceleration, orientation, and magnetic field data from 7 IMUs (MTw Awinda®), as well as a laser signal (processed to provide the distance to the ground over time). In protocol II, two additional signals were recorded: the exoskeleton-user interaction torque and ankle angle. All data were collected at the same frequency (100 Hz) and synchronously. The collected data from IMUs and ankle–foot exoskeleton were pre-processed using low-pass filters at 184 Hz [52] and 5 Hz [53], respectively, to remove high-frequency noise caused by sensor displacements or environmental factors. The data obtained from protocols I and II were grouped, creating the protocol I&II dataset, which was used to create a versatile model capable of decoding LMs in both assisted and non-assisted conditions. The dataset from protocol I&II includes all signals measured by the wearable sensors (MTw Awinda and laser) from protocols I and II but excludes the exoskeleton data.

3.2 Sequence data segmentation

All sensor data was normalized within the range of $[-1;1]$ using the min–max scaling procedure, considering the benchmark of normalization methods reported in [13]. Normalization helps to (i) standardize the scale of the inputs, improving convergence speed and stability of the LSTM model, and (ii) reduce model bias, ensuring that all input data contribute equally.

The normalized data were segmented into sequences based on a specific SL. The sequences are sliding windows that move through the sensor signals with a specified overlap. The SL and the size of the overlap must be carefully selected as they influence the LSTM classification performance. Previous works [54, 55] demonstrated that larger window sizes are usually required to capture the high motion variability found in complex human daily activities. On the

other hand, repetitive activities that involve several body parts are more easily recognized with smaller window sizes. Literature used SLs ranging from 0.5 to 5 s to classify human activity [56]. This work aims to study the most reliable SL for predicting the LMs by assessing the LSTM performance when using 0.6-, 0.8-, 1-, and 1.2-second SLs. The overlap size between sequences was set to half the SL, as proposed in [57]. The data sequences encompass features that will be used in the LSTM training and validation.

3.3 Sequence data labelling

For the data labelling, it is important to first define the critical time. The literature defines the critical time as the latest possible moment until which the control of the assistive device can be adapted to the new LM without disturbing the user [7]. For this study, the critical time corresponds to the moment that the leading leg leaves the first terrain type (i.e., foot contact off from the leading leg). We obtained the critical time by adjusting the experimenter-marked instant in the mobile application according to the user's foot contacts. The foot contacts were retrieved from a gait event detection algorithm developed by our team [58].

We labelled the segmented data according to the 5 LMs associated with 5 numerical classes (i.e., LW-1, RD-2, RA-3, SA-4, SD-5). The labelling procedure considered as ground truth the experimenter-marked LMs transition moments (see Fig. 4 – Marker) that were inspected through the user's foot contacts. It is important to note that this study focuses on predicting LMs, i.e., decoding the LMs before the critical time. Thus, we trained the LSTM to predict an LM before the subject initiates that LM. To achieve this, during the training, the LSTM needs to see kinematic and laser data that precedes the LM to learn how to predict it based on the characteristics of these signals.

Following this approach, the data labels were shifted “backwards” by one sequence length relative the ground truth, as represented in Fig. 4. This method is designed to train the LSTM model on the sequence patterns that precede each LM, enabling it to classify LMs in advance. As an instance, Fig. 4 shows one kinematic signal (right foot gyroscope in the sagittal), exoskeleton data (ankle angle in the sagittal plane), and the laser signal, all synchronized with the ground truth (marker) and the preceding labeling zones.

3.4 Model building

This section addresses the methods used to build the classification models for prediction purposes. This study follows a bioinspired machine learning approach, inspired in the way humans make decisions based on past events in memory when walking in different scenarios. The LSTM was selected due to its ability to hold information from

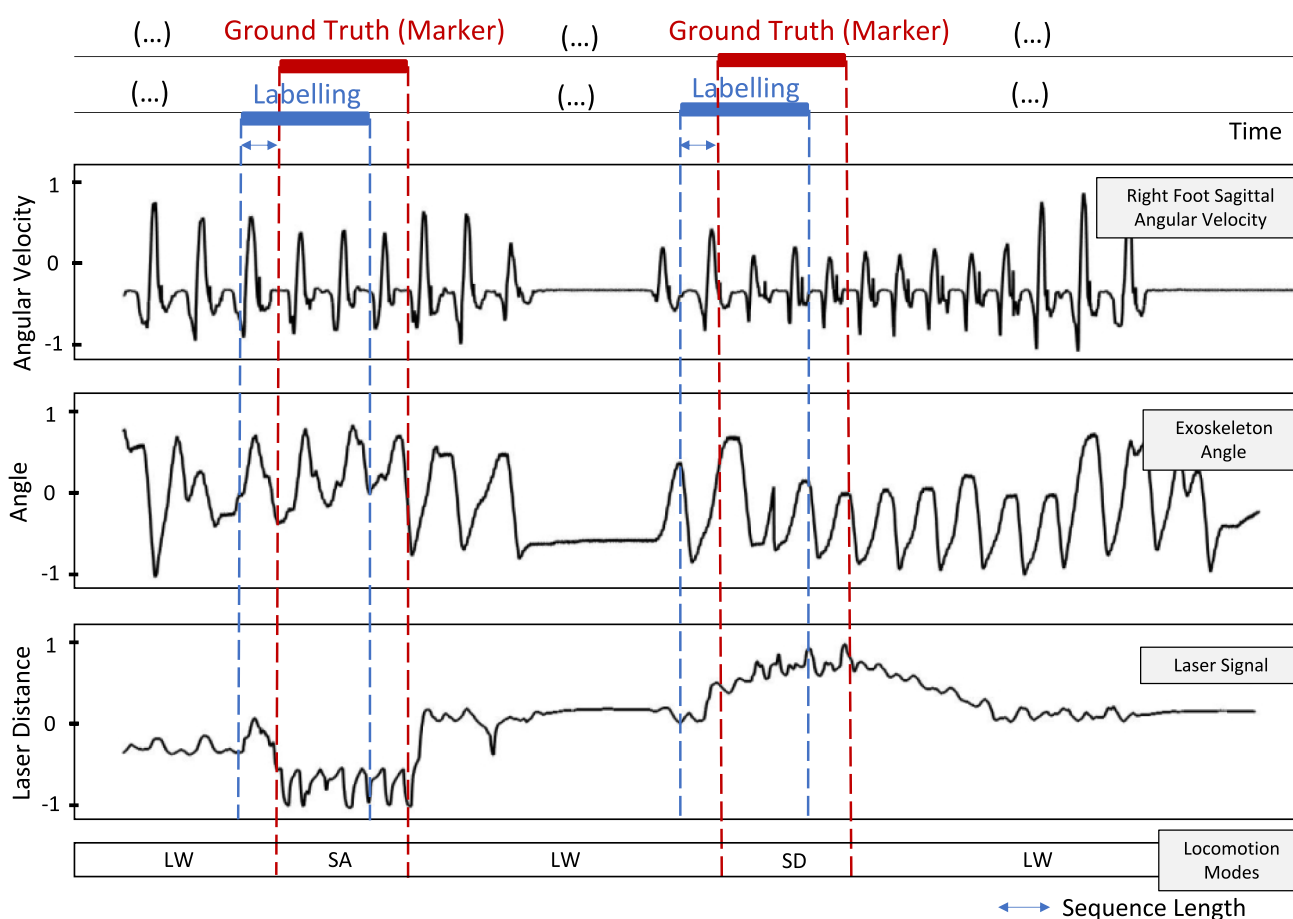


Fig. 4 Ground truth zone (red) and labelling zone (blue) represented in time synced with the right foot gyroscope (sagittal), exoskeleton angle, and the laser signals. The labelling zone precedes the ground truth zone of 1 SL (ranging from 0.6 – 1.2 s) to potentiate the LSTM prediction ability

the past. On top of that, LSTM has a temporal dimension, as it is designed to classify patterns in data sequences, which is essential for classifying upcoming terrains during locomotion.

We used an LSTM architecture composed of 8 layers (illustrated in Fig. 1), including: (i) a sequence input layer; (ii) 2 LSTM layers with 64 hidden units and sequence as output mode; (iii) an LSTM layer with 64 hidden units and last as output mode; (iv) a dropout layer with 0.1 probability; (v) fully connected layer for 5 classes; (vi) a softmax layer; (vii) and a classification layer. The neural network contains 8 nodes and 3 hidden layers with 64 hidden units each, and the dropout rate was set to 0.1. The LSTM loss function is cross-entropy, the learning rate was set to 0.01, and the batch size was 66. This neural network architecture follows previous studies [19, 56], targeting human activity recognition. The LSTM weights were randomly initialized, and the ADAM optimizer was used. Figure 1 demonstrates the LSTM classification procedure based on the sensor data provided as SLs.

Eight classification models were developed by training the LSTM with four different sequence lengths (SLs) (0.6, 0.8, 1, and 1.2 s) for protocols I and II, to identify the optimal SL and the LSTM models with the highest generalization power. Four additional classification models were created using data from protocol I&II by training the LSTM with data from protocols I and II, to determine the versatility of the proposed tool in decoding LMs during assisted and non-assisted walking.

This study randomly divided the collected dataset into two groups: (i) 70% of the dataset for training and validation, and (ii) 30% of the dataset for testing the model performance under unseen data. This approach mirrors the division used in [59]. A 3-fold cross-validation was applied throughout three repetitions, considering a random division for each fold of equal size. The stopping criteria were a maximum of 1000 epochs or an increase in validation loss 6 times larger than the previous smallest loss. The study of the best LSTM model was performed independently for features from protocols I, II, and I&II.

3.5 Performance evaluation

The LSTM model performance was evaluated considering the following metrics. Mathew's Correlation Coefficient (MCC) was employed to assess the model's performance due to its ability to handle unbalanced classes effectively [60]. It is regarded as a balanced assessment metric of classifiers since it considers true and false positives and negatives. The MCC is calculated using Eq. (1),

$$MCC = \frac{(TP \times TN - FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (1)$$

where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives. The MCC value ranges between -1 and 1 , where 1 indicates a perfect prediction, 0 indicates random prediction, and -1 represents total misclassification.

We also computed the F1-score, a metric that combines precision and recall scores, to balance the trade-off between false positives and false negatives. The F1-score is computed through Eq. (2).

$$F1Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (2)$$

Accuracy was evaluated for comparison with the literature's findings. It is a commonly used metric but can be misleading for imbalanced datasets. The accuracy is derived from the confusion matrix using Eq. (3).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

We computed the time in advance to evaluate whether the LSTM tool can predict LMs in advance. This metric is the difference between the critical time and the time the LSTM predicts the LM. Equations (4) presents the formula to compute *Timeinadvance* (in seconds).

$$Time\ in\ advance = Critical\ Time - LM\ Prediction \quad (4)$$

where *LMPrediction* refers to the instant when the LSTM decodes the LM, and *CriticalTime* corresponds to the moment that the leading leg leaves the first terrain type (i.e., foot contact off from the leading leg). Additionally, we computed the stride time and the percentage of stride, which represent the average duration of the gait cycle (in seconds) and the average moment of the gait cycle (in %) at which the prediction occurred, respectively.

3.6 Statistical procedures

We started by verifying the data normality using the Komogorov-Smirnov test. Accordingly, non-parametric

tests were performed. Then, we used the Wilcoxon sign-rank test to determine the similarity between the train and test datasets used in this study. The Friedman test was used to study the influence of the SL on the LSTM classification performance and to verify if there are significant differences in LSTM performance for assisted- and non-assisted walking (protocol I, protocol II, and protocol I&II). This statistical test used the mean accuracy values obtained in the cross-validation for each SL across protocols. Additionally, a Friedman test was conducted to analyze the statistically significant differences in the prediction times obtained in the test results across protocols. When significant differences were found, Wilcoxon signed-rank post-hoc tests were performed. For each analysis, a p -value of 0.05 was deemed significant.

4 Results

This section presents the results obtained from cross-validation and testing procedures. The cross-validation results allow us to identify the best sequence length (SL) and investigate whether the presence of an exoskeleton influences LM prediction. The testing results will demonstrate the generalization ability of the best LM prediction model identified in the cross-validation.

The Wilcoxon sign-rank test reported statistically significant differences between the train and test datasets for protocol I (p -value = 0.028), protocol II (p -value = 0.0015), and protocol I&II (p -value = 0.0029). These results indicate that the test datasets are suitable to determine the LSTM model performance in unseen data.

4.1 Cross-validation results

Table 2 lists the achieved results (accuracy and MCC) for each SL for all protocols, indicating that the SL affects the LSTM performance. The results showed that the 0.8 s and 1 s SLs increased the accuracy by 41% and decreased the accuracy variability (with a standard deviation reduction of 94%) when compared to 0.6 s and 1.2 s SLs. The Friedman test confirmed that the SL significantly influences ($p = 0.0293$) the classification performance. From the Wilcoxon sign-rank test, we found statistically significant differences between the 0.8 s SL with the 0.6 s SL ($p = 0.0312$) and 1.2 s SL ($p = 0.0216$). Similarly, the Wilcoxon sign-rank test revealed statistically significant differences comparing the 1 s SL with the 0.6 s SL ($p = 0.0156$) and 1.2 s SL ($p = 0.0367$).

Regarding LSTM performance across protocols, Table 2 shows that the LSTM achieved a similar mean accuracy between all protocols for 1 -s SL (protocol I- 98.3% accuracy,

Table 2 Cross-validation results in terms of accuracy and MCC (mean $\pm$ std) for protocols I, II, and I&II and all SLs. The highest performances are highlighted. It also presents the number of observations used to build each model

Protocol	Sequence Length (s)	Observations (# Sequences)	Accuracy (%)	MCC
I	0.6	12668	84.7 $\pm$ 3.90	0.532 $\pm$ 0.071
	0.8	9491	96.7 $\pm$ 0.10	0.844 $\pm$ 0.008
	1	7580	98.3 $\pm$ 0.004	0.915 $\pm$ 0.001
	1.2	6306	63.9 $\pm$ 14.14	0.283 $\pm$ 0.124
II	0.6	27575	52.8 $\pm$ 2.20	0.321 $\pm$ 0.017
	0.8	20667	96.2 $\pm$ 0.35	0.857 $\pm$ 0.009
	1	8272	97.5 $\pm$ 0.31	0.899 $\pm$ 0.012
	1.2	13764	37.3 $\pm$ 1.22	0.124 $\pm$ 0.062
I&II	0.6	40243	55.8 $\pm$ 4.45	0.316 $\pm$ 0.033
	0.8	30158	95.7 $\pm$ 0.50	0.831 $\pm$ 0.013
	1	15852	97.8 $\pm$ 1.62	0.899 $\pm$ 0.007
	1.2	20070	47.8 $\pm$ 13.25	0.225 $\pm$ 0.076

protocol II—97.5% accuracy, protocol I&II—97.8% accuracy). Based on the Wilcoxon signed-rank test, there are no significant differences ($p=0.0625$) in the accuracy results between protocols I and II, indicating no significant difference in LSTM performance between assisted- and non-assisted walking. Further, the LSTM accuracy in protocol I&II is closer to that achieved for the other protocols (10% and 3% difference when compared to protocol I and protocol II, respectively).

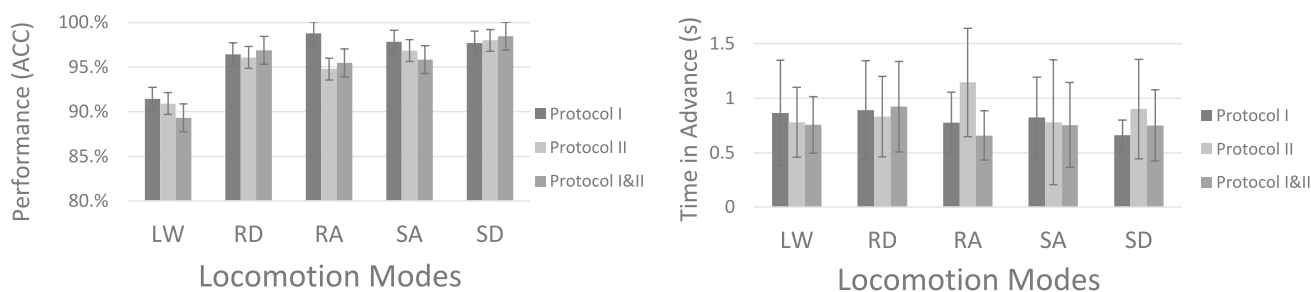
4.2 Testing results

In the testing procedure, we evaluated the LM prediction performance with the 0.8 and 1-s unseen SLs, given the better performance of LSTM for these SLs in the cross-validation. Figure 5 presents the LSTM performance (accuracy and time in advance) for decoding each LM, considering the 0.8 s- and 1 s-SLs. Figure 5 shows that the prediction accuracy stood above 94% for all LMs, considering all protocols and both SLs, except for predicting LW (accuracy ranges from 89 to 92%). LSTM was more effective for predicting stair walking (SA and SD). Moreover, Fig. 5 indicates that, on average, the LSTM predicts in advance 0.66 s, considering a mean stride time of 1.28 ± 0.164 s and 2.677 ± 0.63 s for protocols I and II, respectively.

Table 3 presents the MCC, accuracy, and time in advance of testing results. Table 5 (Appendix I) presents additional metrics, namely the precision, sensitivity, specificity, and F1-score. Figure 7 (Appendix I) shows the confusion matrices for all tested models.

The results of Table 3 suggest consistency of the LSTM for unseen data when compared to cross-validation results, considering that the performance in accuracy and MCC has slightly decreased by 1% and 6%, respectively, for all protocols. A statistical analysis conducted with a Wilcoxon sign-rank test indicated no significant differences between cross-validation and test ($p=0.1250$). Additionally, the use of 0.8 s or 1 s SLs shows a mean difference of 0.2% and 0.4% in accuracy and MCC, respectively, for all protocols.

Performance using 0.8 second sequence length



Performance using 1 second sequence length

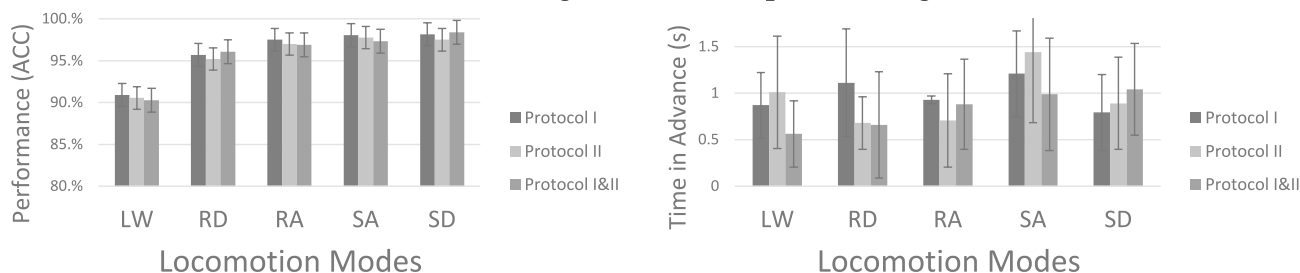


Fig. 5 LSTM performance in test procedure per LM for all protocols using the 0.8 s-SL and 1 s-SL

Regarding the LSTM performance across protocols, Table 3 shows that the performance (accuracy and MCC) of protocol I only differs 0.8% from the one obtained for protocol II. This suggests that the LSTM model was able to maintain its prediction ability in assisted and non-assisted conditions. Additionally, the LM prediction using mixed datasets (protocol I&II) presented promising results, with accuracy values above 95% for the 0.8 and 1 s SLs, while revealing reduced differences to protocols I (0.7%) and II (0.03%). The models from protocol II enabled predictions with higher advance in time (0.92 s). Despite that, a Wilcoxon sign-rank test indicated no significant differences in advance time between protocols ($p=0.3438$), i.e., between assisted and non-assisted conditions. Additionally, protocol II has a higher stride duration when compared to protocol I. Thus, in terms of the gait cycle, LSTM predicts the LMs earlier in protocol I (non-assisted) than in protocol II (assisted walking).

We evaluated the LSTM's computational load through preliminary tests conducted in the CCU (the Raspberry Pi 4b, Quad core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5 GHz, 4 Gb RAM). These tests revealed that, on average, the LSTM required 2 ms to make an LM prediction in real-time conditions.

Figure 6 presents sensor signals from a representative subject performing the real-life circuit. It shows the changes in kinematic data (angular velocity) and the environmental context data (infrared laser) when terrain changes occur. The bottom graphic of Fig. 6 depicts the actual and predicted classes related to the executed LMs. This bottom graphic demonstrates that the predicted classes of the LSTM anticipate the actual classes (unshifted ground truth) when the transition between LMs occurs.

An additional study was conducted to determine the most meaningful source of data from sensors selected by the LSTM models, across protocols, for the 0.8 s and 1 SLs. Figures 8, 9, and 10 (Appendix I) present the activation weights of each feature. These results indicate that the laser features do not present higher relevance than IMU-related features. The activation weights for laser features (-0.078 , and -0.205 (protocol I), -0.095 , and -0.048 (protocol II), -0.180 , and -0.203 (protocol I&II)), suggest a reduced relevance of the laser sensor in predicting LMs. Further, results

for protocol II indicate the highest relevance of IMU-based features regarding the exoskeleton's signals.

5 Discussion

This study has developed a more accurate and time-effective tool for predicting LMs in both assisted and non-assisted conditions compared to our previous work [13], which relied solely on kinematic data. Although the proposed LSTM used both kinematic and laser data, the results presented in Figs. 8, 9, and 10 indicate the reduced relevance of the laser sensor within the LSTM model. This finding does not support our hypothesis that the anticipatory nature of environment awareness data would enhance the prediction ability. Moreover, the longer prediction lead time achieved by the proposed tool (Table 3 and Fig. 6), compared to previous studies in both assisted [18, 37, 39] and non-assisted conditions [12, 38, 42, 43], supports our hypothesis that the LSTM's inherent ability to retain time-history information enhances the anticipatory nature of LM decoding.

5.1 Analysis of SL effects

This study verified that the SL affects the LSTM prediction performance; thus, it should be carefully selected, as reported by [54, 55]. The analysis of the results from Table 2 and the statistical results indicated that the 0.8 s and 1 s SLs prompt more accurate predictions, for assisted and non-assisted walking, when compared to 0.6 s and 1.2 s SLs. This finding suggests that 0.8 s and 1 s SLs hold more meaningful information than the remaining SLs for decoding LMs. Further, the results of Table 3 report that the 1 s SL predicts in advance (12%) when compared to the 0.8 s SL. Overall, 1-s SL is the best SL for this application. This result is in line with the literature findings, in which similar SL (1-s window) achieved high classification performances to decode static, dynamic, and transition activities at self-selected speeds [42]. Note that when performing in real-time, the LSTM is only able to start the prediction upon the data collection of one 1 s-SL.

Table 3 Test performance for protocols I, II, and I&II (mean $\pm$ std values)

Protocol	Sequence Length (s)	Accuracy (%)	MCC	F1-score	Time in advance (s) $\Rightarrow$ Mean Percentage of Stride (%)
I	0.8	96.4 $\pm$ 0.05	0.833 $\pm$ 0.01	0.914 $\pm$ 0.01	0.803 $\pm$ 0.346 $\Rightarrow$ -2.54%*
	1	96.1 $\pm$ 0.02	0.833 $\pm$ 0.01	0.905 $\pm$ 0.04	0.984 $\pm$ 0.368 $\Rightarrow$ -16.64%*
II	0.8	95.3 $\pm$ 0.15	0.823 $\pm$ 0.02	0.889 $\pm$ 0.08	0.887 $\pm$ 0.444 $\Rightarrow$ 26.87%
	1	95.6 $\pm$ 0.24	0.826 $\pm$ 0.03	0.895 $\pm$ 0.03	0.946 $\pm$ 0.528 $\Rightarrow$ 24.67%
I&II	0.8	95.2 $\pm$ 0.24	0.820 $\pm$ 0.03	0.886 $\pm$ 0.01	0.769 $\pm$ 0.324 $\Rightarrow$ 21.17%
	1	95.8 $\pm$ 0.11	0.826 $\pm$ 0.01	0.899 $\pm$ 0.05	0.827 $\pm$ 0.538 $\Rightarrow$ 18.24%

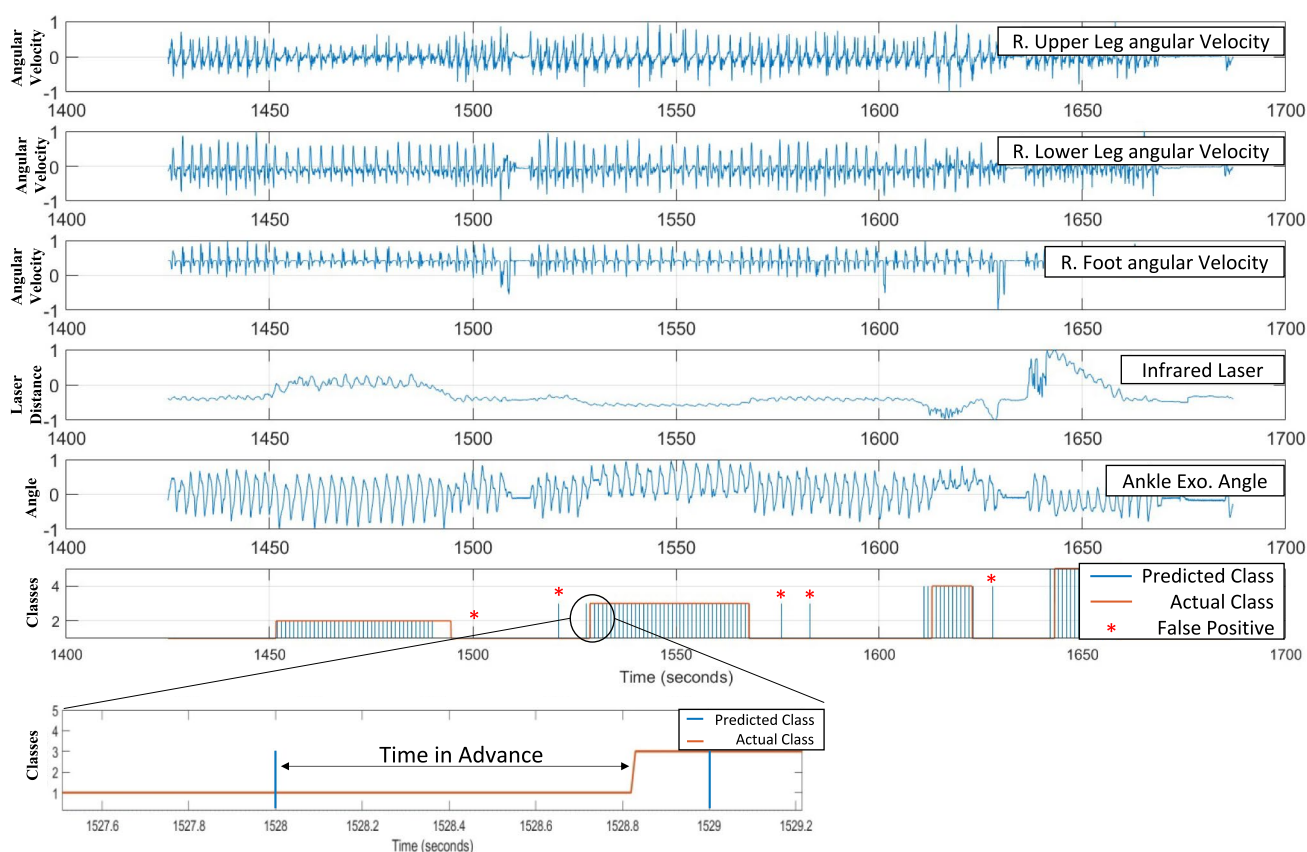


Fig. 6 LM Prediction performance of one representative test trial, showing the predicted, the actual classes (LW-1, RD-2, RA-3, SA-4, SD-5), and the false positives. The actual classes start, and end occur in LM transitions (critical time) Signal examples segmented in sequence features are presented, namely, right upper leg angular velocity (sagittal), right lower leg angular velocity (sagittal), right foot angular velocity (sagittal), the infrared laser, and the exoskeleton ankle angle. The bottom graphic describes what is the time in advance for one specific LM prediction

5.2 Analysis of cross-validation and test results

The comparison between cross-validation (Table 2) and testing (Table 3) results indicates a small decrease in the accuracy (1.5%) and MCC (6%) for all protocols in the test procedure. We observed a higher decrease in MCC metric compared to accuracy possibly due to the higher influence of unbalanced classes in the testing dataset. However, these differences are not significant ($p=0.1250$). This finding demonstrates the high consistency of the LSTM performance between cross-validation and test procedures and that the models are unbiased and well-generalized for both assisted and non-assisted conditions.

The class that prompted the highest classification error was the LW, with an accuracy of 92%. It may be related to the possible confusion between LW and RA/RD predictions. This misclassification is perceptible when analyzing the confusion matrices and may occur due to the low ramp inclination, as verified in similar studies [7, 32]. Nevertheless, the prediction of the remaining LMs stood above 94% accuracy, considering all protocols and indoor and outdoor conditions, as expected in daily assistance.

5.3 Comparison between assisted and non-assisted conditions

The findings suggest that the use of a neural network with the ability to hold time-history information in memory, such as the LSTM, is a well-suited approach to decode LMs commonly found in real-life scenarios. The applied LSTM architecture demonstrated highly promising results (accuracy = 98.28%), similar to the study conducted by Zhao et al. [56], in which a residual bidirectional LSTM (accuracy = 90.20%) outperformed other classifiers, such as LDA (accuracy = 69%) and CNN (accuracy = 85.1%) in human activity recognition. Furthermore, the minimal and non-significant differences in accuracy ($p=0.0625$) between protocol I&II, protocol I (10%), and protocol II (3%) revealed that the proposed tool stands more versatile than other LM decoding tools that can only be used with assistive devices [18, 19, 40, 41]. These findings demonstrate the reliable use of the proposed LSTM in assisted and non-assisted walking; suggesting that it may have the potential to be successfully applied in walking assisted by other devices and may not require device-specific tuning.

Regarding the ability to predict in advance, no significant differences ($p = 0.3438$) were found between assisted and non-assisted walking. However, the instant in the gait cycle in which the predictions are issued is different. For protocol I (non-assisted walking), the LMs were predicted at 90% of the previous gait cycle to the LM transition. On the other hand, in protocol II (assisted walking), the LMs were predicted, on average, at 26% of the gait cycle where the LM will occur, but before the critical time (which occurs around 60% of the gait cycle). These results indicate that the presence of the exoskeleton delayed the prediction, which might be caused by gait asymmetries related to unilateral assistance. Despite this, in protocol I&II, the prediction occurred around 20% of the gait cycle (similar to protocol II), suggesting the good adaptability of the LSTM to both assisted and non-assisted conditions.

5.4 Related work in non-assisted LM decoding

The proposed LSTM model with 1 s-SL innovates the literature tools for non-assisted walking [12, 38, 42, 43], listed in Table 1, by predicting the LMs with higher accuracy (accuracy = 98%) and greater advance (> 0.66 s for 1.98 ± 0.833 s of mean stride time). Further, our tool predicts the five LMs using a single classification model, advancing the strategy proposed by [13] and [38] that rely on sequential classification models, in which the misclassification propagates through the levels and presents higher computational load than our model (2 ms).

5.5 Related work in assisted LM decoding

Our LM prediction tool advances upon the recognition tools proposed for assisted walking by prosthesis [20, 32, 44, 61] by presenting more accurate results (accuracy around 96%) in both assisted and non-assisted conditions and by enabling the participants to execute the LM transitions using their self-selected limb. Although previous studies have proposed highly accurate LM decoding tools, studies [19, 34, 35, 45–47] focus on LM recognition rather than prediction in exoskeleton-assisted walking.

By comparing with prediction tools for exoskeleton-driven assistance, our LSTM tool improves upon the work of [18] by predicting five LMs (LW, RA, RD, SA, SD) with higher accuracy (accuracy of 95.6% against 90%) and incorporating inertial data from a larger pool of participants (10 against 3 subjects); thus, creating a model with more heterogeneous gait patterns. Our strategy achieved generalization for a given set of subjects; consequently, it seems to have the potential to be applied to further healthy individuals without requiring tuning. Moreover, our proposal predicted greater advance (> 660 ms)

than the literature studies: [18] ($< 185.33 \pm 56.32$ ms), [37] ($< 78.5 \pm 25.0$ ms), and [39] (< 353 ms). The LSTM predictions occurred until 27% of the stride, indicating high anticipation regarding the critical time (stands at 60% of the stride). This finding considers that in the literature the critical time occurred at the mid-swing of the leading leg while we set the critical time as the foot-off contact event. It is preferable that the LMs are detected before starting the swing phase to ensure enough time to smoothly and timely adapt the exoskeleton to the LM transition and the upcoming LM. Finally, our tool predicts the five LMs in advance, which was not reported for tools proposed for LM prediction in exoskeletons [18, 37, 39] where some LMs were decoded after the critical time.

5.6 Limitations

The proposed strategy was validated with ten able-bodied participants, and promising results were achieved. However, validation procedures considering continuous daily use with a higher number of participants are needed. We anticipate validating the exoskeleton with the proposed LM prediction tool with pathological end-users following the procedure described in this study. Further developments will investigate the minimal sensor setup by analyzing the existence of redundant data and consequently removing unnecessary sensors. To this end, Graph Neural Networks can be explored to investigate spatial relationships between on-body sensors and potentially identify redundant or less significant sensors without losing important information. Moreover, the LSTM's computational load (2 ms) to make predictions in real-time meets the timing requirements of the robotic device control loop (every 10 ms). This finding indicates the LSTM's feasibility for future integration into the high-level control of the ankle–foot exoskeleton.

6 Conclusions

This study demonstrated that the LSTM with a 1 s SL, mostly relying on kinematic data rather than environment-aware data, can timely and accurately predict five LMs commonly encountered in real-life scenarios, under both assisted and non-assisted gait. The use of an LSTM advanced our previous non-deep learning tool and literature tools by predicting with greater advance time. This work advances the field by presenting a more versatile prediction tool that: (i) may be applied with or without exoskeleton and potentially among different assistive devices without requiring device-specific tuning; (ii) enables the user to self-select the limb to perform the LM transitions, providing a more natural gait. These findings support the transfer of this decoding tool to daily living settings in the presence or absence of an assistive device.

Appendix

Table 4 presents the main specifications of sensor systems used for data collection.

Table 5 presents additional metrics regarding the test procedure considering the use of the 0.8 s and 1 s SLs for all protocols.

Table 4 Main specifications of the use sensor systems for data collection

	Mtw Awinda® [62]	TFMini Lidar® [16]
Sensors (features)	7 wireless IMUs. Each sensor includes: 3D linear accelerometers ($\pm 160m/s^2$; 0.5% of FS); 3D rate gyroscopes ($\pm 2000^\circ/s$; 0.1% of FS); 3D magnetometers (± 1.9 Gauss; 0.1% of FS); barometer (300–1100 hPa; 0.05% of FS)	Infrared laser resolution of 5 mm; operative range [0.3 – 12] m for indoor and [0.3–7] m for outdoor conditions
Dimensions	47 mm × 30 mm × 13 mm	42 mm × 15 mm × 16 mm
Weight	16 g	6.1 g
Sampling rate	1000 Hz	100 Hz
On-board processing	Calibration, Low-pass filter at 184 Hz, SDI algorithm	Calibration,
Communication protocol	Awinda protocol (2.4 GHz ISM chipset)	UART
Output frame rate	100 Hz	100 Hz
Latency of communication	9.5 ms – 19 ms	NA
Autonomy	6 h	12 h

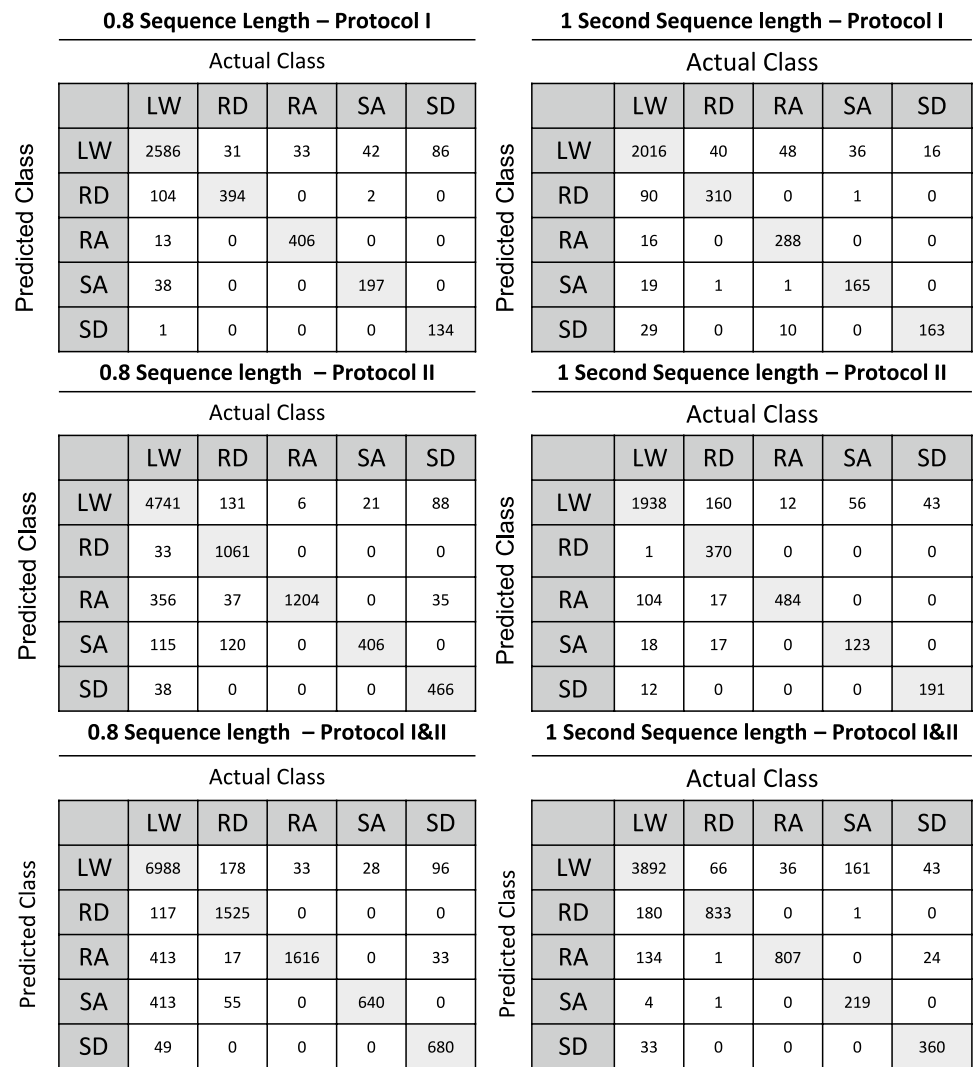
Table 5 Additional performance evaluation metrics (precision, sensitivity, specificity, f1-score) for the test results, considering protocol I, II and I&II

Protocol	Sequence Length (s)	Precision	Sensitivity	specificity
I	0.8	0.9137	0.9137	0.9784
	1	0.9055	0.9055	0.9764
II	0.8	0.8894	0.8894	0.9723
	1	0.8954	0.8954	0.9738
I&II	0.8	0.8857	0.8857	0.9714
	1	0.8993	0.8993	0.9748

Figure 7 shows the confusion matrices obtained from the test procedure, considering the use of the 0.8 s and 1 s SLs for all protocols.

The LSTM activation weights provide an understanding of the relative relevance of the used features in classifying LMs. The neural network weights range from -1 to 1. A positive weight represents an excitatory connection whereas a negative weight represents an inhibitory connection. Therefore, weights closer to 1 represent a strong excitatory feature while weights closer to -1 represent a strong inhibitory feature. Figure 8, 9 and 10 represent the feature weights sorted between 1 and -1 for the 0.8- and 1-s SLs considering protocols I, II, and I&II.

Fig. 7 Confusion matrices of the test phase for the 0.8 s and 1 s-SLs of protocol I, II and I&II



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