Real-Time Torque Estimation Using Human and Sensor Data Fusion for Exoskeleton Assistance*

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Abstract. Robotic assistive devices have emerged as a potential complement for repetitive and user-centered gait rehabilitation. In this field, the development of electromyography (EMG)-based torque controls has played a crucial role in improving the user experience with robotic assistive devices. However, most existing approaches for EMG-based joint torque estimation (i) are designed for upper limbs; (ii) often do not consider the complexity of the walking motion, focusing only on the stance phase; and (iii) rely on complex mathematical models that result in time-consuming estimations. This study aims to address these shortcomings by evaluating the generalization ability of a Deep Learning regressor (Convolutional Neural Network (CNN)) for estimating ankle torque trajectories, in real-time. Several inputs were incorporated, namely, EMG signals from *Tibialis Anterior* and *Gastrocnemius Lateralis*, hip kinematic data in the sagittal plane (angle, angular velocity, angular acceleration), walking speed (from 1.5 to 2.0 km/h), user's demographic (gender and age) and anthropometric information (height and mass, ranging from 1.50 to 1.90 m and 50.0 to 90.0 kg, respectively, and shank and foot lengths). Results showed that a CNN model with two convolutional layers showed the highest generalization ability (Root Mean Square Error: 23.4±8.36, Normalized Mean Square Error: 0.494±0.299, and Spearman Correlation 0.754±0.105). CNN model's time-effectiveness was tested in an active ankle orthosis, being able to estimate ankle joint torques in less than 2 milliseconds. This study contributes to a more time-effective model for real-time EMG-based torque estimation, enabling a promising advancement in EMG-based torque control for lower limb robotic assistive devices.

Keywords: Deep Learning, Electromyography, Human-Robot Interaction.

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1 Introduction

Restoring the motor function of individuals with lower limb impairments is of utmost importance, enabling them to regain independence in performing daily living activities and enhancing their overall quality of life. At this level, robotic assistive devices, such as active orthoses and exoskeletons, have been suggested in the rehabilitation field to serve as a complement to conventional physiotherapy, to improve the movement coordination and muscular function of motor-disabled patients [1]. For that, trajectory tracking controls (such as position control strategies) have been widely used [2]. According to [2], although these control strategies impose repetitive gait training, they are prone to result in less safe and comfortable strategies for the users since high forces can be done by the robotic assistive device when the human-robot interaction is low.

Different control approaches have been suggested in the last years to enable a more smoothly use of the robotic assistive device by the user. In this field, electromyography (EMG)-based torque controls have been developed [3]. Despite the use of EMG sensors has disadvantages related to the movements between the skin and the EMG sensors, the correct placement of the electrodes may empower torque control, since EMG signals can be measured before the muscle contraction [3]. Several methods have been proposed for EMG-based torque estimation to control a robotic assistive device [4–16]. Despite being a valuable contribution to EMG-based control, most of the developed methods (i) were not developed for lower limbs [12–16]; (ii) did not encompass the walking motion [7, 8]; (iii) those that consider walking, did not estimate the torque for the entire gait cycle, focusing only on the stance phase [6–8]; (iv) depend on user- and muscle-specific parameters (such as muscle-tendon unit, pennation angle, optimal fiber length, optimal length of the tendon, musculotendon length, and moment arm) that are difficult to measure [4, 5, 9–11]; (v) did not present the time required to perform a single joint torque estimation [6, 12–16]. For instance, the neuromusculoskeletal model proposed in [5] lasted 63 ms to estimate the knee joint torque. The use of this method will entail a control frequency of approximately 2 Hz (below the gait frequency), which is not feasible for controlling an exoskeleton for gait rehabilitation.

To the best knowledge of the authors, there is no method able to estimate the joint torque in a time-effective manner for real-time control of an exoskeleton without depending on time-consuming calibration steps and muscle-specific parameters. This study proposes a Deep Learning (DL) method for the real-time EMG-based ankle joint torque estimation during walking, according to the measured user's anthropometry and demographic data, speed, and joint kinematics data. The ankle joint was selected since it is a commonly affected lower limb joint in neurological diseases [17]. This study extends teamwork [17] by optimizing the prediction performance of the DL method and by integrating it into SmartOs - Smart, Stand-alone Active Orthotic System, to assess its time-effectiveness for real-time torque estimation [18]. We hypothesize that the estimated ankle joint torque can be obtained in less than 63 ms, without considering kinematic information.

2 Materials and Methods

2.1 SmartOs Architecture

SmartOs is a modular framework hierarchically structured, following a non-centralized architecture (Fig. 1). This architecture consists of (i) a Central Controller Unit (CCU) responsible for managing the communication between all modules of the system and for running gait analysis tools and high-level controllers at 100 Hz; and (ii) three development boards with lower computational capabilities. These boards consist of: (i) the Low-Level Orthotic System (LLOS), which interfaces with the active ankle orthosis (Exo-H2 - Technaid, Madrid, Spain [19]) through Control Area Network (CAN) protocol and manages the low- and mid-level controllers within the hierarchical control architecture [18]; (ii) the Wearable Motion LAB, which handles the real-time data acquisition of team-developed sensor systems (such as InertialLab used in this study) [18, 20, 21]; and (iii) the Wearable Biofeedback System, which handles the biofeedback systems (auditory and vibrotactile cues embedded in the system) [22]. Further, SmartOs embodies two user-friendly graphical applications: the mobile application for selecting the therapy settings and the desktop application for real-time and/or offline visualization of therapy data. Further details are presented in [18].

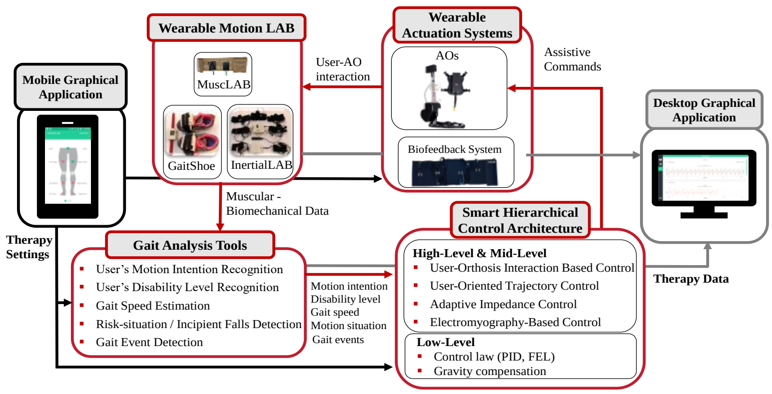

Fig. 1. Design of SmartOs modular framework.

The CCU corresponds to an UDOO X86 computer with an Intel® Celeron N3160 up to 2.24 GHz processor and a Random Access Memory with 4.0 GB. The development boards are the STM32F4-Discovery board (STMicroelectronics, Switzerland), running at 168 MHz, and communicate with the CCU by UART interface. Furthermore, the active orthosis consist of an electrical actuator (EC60 100W Flat Brushless (Maxon, Germany), 100W and a maximum efficiency of 86 %) coupled to a gearbox (CSD-20-160-2A-GR (Harmonic Drive, Japan) with a gear ratio of 160:1, and a maximum efficiency of 55 %) able to provide an average and peak torques of 35 N.m and 180 N.m, respectively [18, 19]. The power supply system consists of a lithium iron phosphate battery (LifePO4) with a voltage of 22.4 V and a capacity of 12 Ah. This battery provides a minimum of 8 hours of autonomy and is equipped with a hardware interface to supply power to all modules of SmartOs, operating at 5 V. All these hardware components are mounted inside a backpack to make the system comfortable and practical to use (Fig. 2).

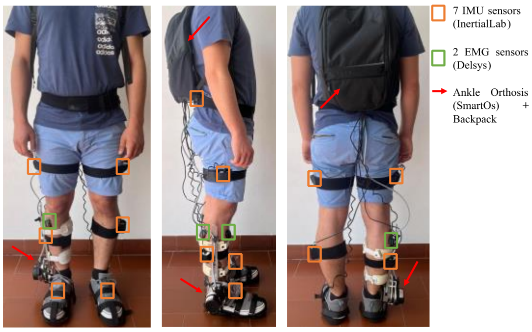

Fig. 2. Male participant instrumented with SmartOs, InertialLab, and Delsys systems, all combined for real-time ankle joint torque estimation.

2.2 EMG Delsys System Integration

To measure and record the EMG muscle activity during the walking motion, the surface 8-channel Delsys Trigno wireless EMG system (Delsys, MA, USA) was used [23]. In our study, this device was integrated into SmartOs system by using the Trigno SDK, to enable the real-time acquisition of EMG signals during the orthosis' use [23]. For that, a Transmission Control Protocol/Internet Protocol (TCP/IP) was implemented to communicate between both systems (CCU of SmartOs system and the Base Station of Delsys system). To decrease the amount of data to be sent via TCP/IP and to work with cleaner EMG signals, the Root Mean Square (RMS) mode of the Delsys system was configured (Avanti-Only Modes: 83) [23]. This mode enables the acquisition of rectified EMG signals with a frequency of 148 Hz, by applying the RMS method. By default, the Trigno SDK sends 27 EMG samples at every 0.0135 s (74 Hz). These samples were reprocessed in SmartOs system by using the RMS at 74 Hz [24].

2.3 Development of DL regression model

Participants. A walking dataset was collected to create the DL regression model. The study involved 17 healthy participants (9 females and 8 males) with a mean body height of 168.0 ± 10.31 cm, a mean body mass of 70.11 ± 14.26 kg, and a mean age of 28.05 ± 3.66 years. Efforts were made to include a stratified anthropometric distribution in an attempt to consider eventual gender biomechanical differences [25].

Instrumentation and Data Collection. Although the ankle joint is the focus of this study, the joint kinematics and kinetics of the three lower limb joints were recorded using a motion-capture system with twelve cameras (Oqus; Qualysis – Motion Capture System, Göteborg, Sweden) and a Force Plate-Instrumented Treadmill (Side-by-Side Treadmill – AMTI, MA, USA), respectively, at 200 Hz.

EMG signals were acquired at 2000 Hz, using 8 surface EMG electrodes from the Trigno system (Delsys, MA, USA). The sensors were attached to the participants' skin following the SENIAM recommendations, acquiring signals from the *Vastus Lateralis* (VL), *Biceps Femoris* (BF), *Gastrocnemius Lateralis* (GAL), and *Tibialis Anterior* (TA) [26]. More information can be found in [27].

Protocol. The protocol started by collecting the gender, age, body mass, height, and shank and foot lengths of each participant. To normalize the EMG data, two maximum voluntary contractions (MVCs) were subsequently performed for each muscle. Finally, each participant was instructed to walk for 4 minutes on the instrumented treadmill, performing 2 minutes at 1.5 km/h and then 2 minutes at 2 km/h.

Data Processing. The kinematics recorded by the motion capture system were filtered using a fourth-order lowpass zero-lag Butterworth filter with cut-off frequencies of 6 Hz. The EMG signals were filtered using the same filter with cut-off frequencies of 20 and 450 Hz. The kinematic and kinetic data were then processed in the Visual3D software to calculate the joint angles and torques of the lower limbs. This calculated torque corresponds to the ground truth of torque data used to build the DL regression models. Additionally, the first and the last 30 seconds of each walking speed were removed from the dataset, to avoid possible irregularities caused by the adaptation to the walking speed. Thus, 1 minute of data in each walking speed was used to train the DL tool.

Regression Models. In this study, a Convolutional Neural Network (CNN) was implemented and evaluated by using Matlab® (2022a, The Mathworks, MA, USA). The CNN was chosen since it provided the best performance across a benchmark analysis in a previous teamwork study [17, 28].

Concerning the CNN, the data were organized by sequences composed of X columns and K lines. While the X represents the number of samples organized sequentially by time and participants, the K lines represent the 9 or 12 inputs (depending if kinematic data are included or not). We studied the CNN performance for ankle torque estimation with and without kinematic data, creating two types of datasets. One dataset had 9 inputs, namely the EMG signals from GAL and TA (normalized by the MVC), walking speed, shank and foot length, body mass and height, gender, and age. The second dataset included the same data with addition of the joint kinematic data (joint angle, angular velocity, and angular acceleration in the sagittal plane), resulting in 12 inputs. The GAL and TA muscles were chosen since they are the muscles more responsible for the ankle joint movement [17, 28].

We conducted an empirical analysis to select (i) the kernel size (2, 10, 20, 40, 60); (ii) the number of convolutional layers (1, 2, 3, 4); (iii) the number of filters per convolutional layer (8, 16, 32, 64, 128); (iv) the sequence length (this means, the value of

X) (40, 50, 60, 80, 100, 120, 150); (v) the batch size (50, 100, 150); and (vi) the dropout value (0, 0.25, 0.50, 0.75). The normalization method was also studied among max-min, z-score, and robust normalization methods. Furthermore, the rectified rectilinear unit (ReLU) function was used for convolutional layers and the adaptive moment estimation optimization algorithm based on the mean square error was used to update the weights and biases of the CNN. This empirical analysis was conducted through the leave-one-subject-out cross-validation (LOSOCV) procedure. Of the seventeen subjects who participated in this study, one subject (female with 27 years old and a body mass and height of 73.4 kg and 1.63 m, respectively) was randomly selected to test the final model. Thus, the model was trained with data from 16 subjects.

2.4 Integration of DL regression model into SmartOs

Once the CNN model was trained and created, it was integrated into the CCU of SmartOs. Considering that the CCU main project is programmed in C++, and the DL regression model was created in Matlab, we had to convert the CNN model to the Open Neural Network Exchange (ONNX) format to enable the easy model transference between programming languages [29]. After being converted to ONNX, the CNN model was integrated into the C++ Project of the SmartOs' CCU to receive the EMG and kinematics data from the Delsys and InertialLab systems, respectively, as well as the anthropometric, demographic and speed information send by the mobile application. From these data, the CNN model was inferenced inside SmartOs system by employing the ONNX Runtime library – a Cross-Platform Accelerated Machine Learning [29].

2.5 Model Evaluation

Four evaluation metrics were employed to evaluate the CNN's performance, namely, the RMS Error (RMSE), the Normalize Mean Square Error (NMSE), the Spearman Correlation (SC), and the prediction time. The first three metrics were computed between the predicted and the real (ground truth) ankle joint torque trajectories during the LOSOCV and the final model testing procedures (both performed in a Hewlett-Packard computer with an Intel® Core™ i7-4710MQ CPU @ 2.50 GHz processor and a Random Access Memory with 16.0 GB).

Further, we have performed an experimental protocol to evaluate the real-time performance of the CNN in SmartOs, namely its prediction time (in a UDOO X86 computer (CCU of SmartOs). This protocol involved one healthy and adult male participant (27 years old) with a body height of 1.70 m and a body mass of 81.2 kg. The participant was instrumented with (i) two EMG sensors from Delsys system, acquiring EMG data from the TA and GAL muscles of the right limb (the lower limb instrumented with active orthosis); (ii) 7 IMUs from the InertialLab system positioned on both feet, shanks, thighs, and torso, assessing the ankle, knee, and hip joint angles of the right and left sides (although only 2 IMUs were required (torso and right thigh) to monitor the hip angle) [20]; (iii) SmartOs system to perform ankle joint torque estimations in the CCU that controls the ankle orthosis. All systems are exhibited in Fig. 2. The EMG and the InertialLab data were used in the CNN at 100 Hz.

At the beginning, the participant's gender, age, body mass, height, leg length and foot length were measured and introduced in the mobile application of the SmartOs system. Then, the participant performed two MVCs for each muscle (TA and GAL) to normalize the EMG data. After that, the participant was instructed to perform a 5-s standing calibration trial for calibrating the InertialLab system. At last, the participant walked on the instrumented treadmill for 5 minutes at 1.5 km/h.

3 Results

3.1 Regression Models Evaluation

Table 1 presents the best results achieved during the LOSOCV method, using the Hewlett-Packard computer. In Table 1, two types of results are presented: results for torque estimation using (i) EMG, anthropometric, demographic, and speed data; and (ii) EMG, anthropometric, demographic, speed, and kinematic data (joint angle, angular velocity, and angular acceleration of the sagittal plane), testing knee and hip kinematic data. The ankle kinematics were not considered because it is affected by the motion of the active ankle orthosis, i.e., the ankle kinematics could result from the human and/or robot motion. Thus, the user’s ankle joint torque estimation could be jeopardized.

Table 1. RMSE, NMSE, and SC metrics for LOSOCV procedure

<table>
<tr><th>Input Data</th><th>Hyperparameters</th><th>RMSE (N.m)</th><th>NMSE</th><th>SC</th></tr>
<tr><td>EMG, anthropometric, demographic, and speed data</td><td rowspan="3">Kernel size: 40
CNN layers (filters): 4 (16, 32, 64, 128)
Dropout: 0.5
Sequence length: 100
Batch size: 100</td><td>23.2±8.35</td><td>0.602±0.615</td><td>0.703±0.242</td></tr>
<tr><td>EMG, anthropometric, knee kinematics, demographic, and speed data</td><td>22.4±9.79</td><td>0.492±0.391</td><td>0.790±0.092</td></tr>
<tr><td>EMG, anthropometric, hip kinematics, demographic, and speed data</td><td>20.2±4.44</td><td>0.390±0.267</td><td>0.802±0.054</td></tr>
</table>

Considering the different combinations of input data, the results suggested that the CNN achieved high generalization ability, characterized by the high mean and low standard deviation values for all evaluation metrics when EMG, anthropometric demographic, speed, and hip kinematic data are used as input. Taking into account this combination of inputs, the number of convolutional layers was deeply studied since these layers have a strong impact not only on the performance of the model but also on the prediction time [30].

Table 2 exhibits the CNN performance for both LOSOCV and final testing procedures when varying the number of convolutional layers. LOSOCV results pointed out that CNN performance reduces as fewer convolutional layers are employed. However, different results were achieved for the final testing procedure, where the CNN reached the best performance when only two convolutional layers were used. For that model, the real and the predicted joint torques of the test dataset were graphically analyzed, being depicted in Fig. 3. Based on Fig. 3, a high level of similarity between the monotony of both curves is reached, confirmed by the SC value (0.846). From Table 2 and Fig. 3, we verified that the RMSE values (slightly above 20 N.m) are associated with the fact that the model cannot achieve the maximum signal magnitude.

Table 2. RMSE, NMSE, and SC during the LOSOCV and final test procedures. The best test metrics were obtained using 2 convolutional layers

Input Data	Convolutional layers (filters)	RMSE (N.m)		NMSE		SC	
		LOSOCV	Test	LOSOCV	Test	LOSOCV	Test
EMG, anthropometric, demographic, speed, and hip kinematics data	4 (16, 32, 64, 128)	20.2±4.44	27.0	0.390±0.267	0.454	0.802±0.054	0.857
	3 (16, 32, 64)	21.4±4.74	27.2	0.469±0.323	0.459	0.781±0.062	0.841
	2 (16, 32)	23.4±8.36	20.5	0.494±0.299	0.261	0.754±0.105	0.846

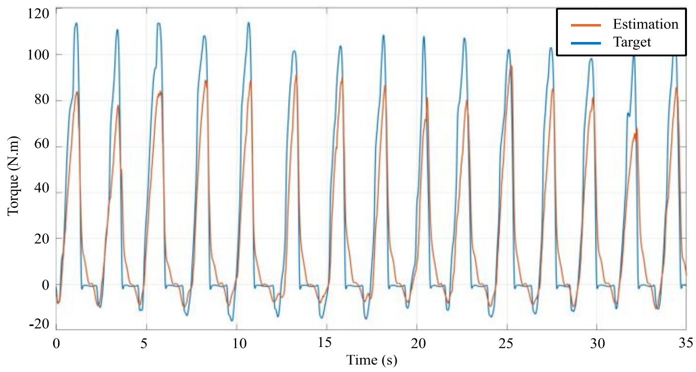

Fig. 3. Real and predicted ankle torques for the test subject (female with 27 years old, body mass and height of 73.4 kg and 1.63 m, respectively), using a CNN with 2 convolutional layers.

3.2 Real-time performance of Regression Models

To complete the CNN model evaluation, we have assessed, in the real experiments, the prediction time of the three CNN architectures (with 2, 3, and 4 convolutional layers), all integrated into SmartOs framework, i.e., into the UDOO x86. Results presented in Table 3 show that there is a high difference in the prediction time when the number of convolutional layers vary, being achieved the lowest time (2 ms) when two convolutional layers are used.

Since the high-level of SmartOs system works at 100 Hz, i.e., every 10 ms, the torque estimation performed by the CNN architecture with two convolutional layers is the only one that complies with that operating frequency. For that model, it is depicted in Fig. 4 the estimated ankle joint torque along with the ankle joint angle recorded by InertialLab system, and the EMG signals of TA and GAL recorded by Delsys system. Based on Fig. 4, we can infer that the ankle joint torque pattern estimated in SmartOs is similar to the one presented in Fig. 3.

Table 3. RMSE, NMSE, and SC for the test subject

Input Data	Convolutional layers (filters)	Mean prediction time (ms/sample)
EMG, anthropometric, demographic, speed, and hip kinematics data	4 (16, 32, 64, 128)	42
	3 (16, 32, 64)	29
	2 (16, 32)	2

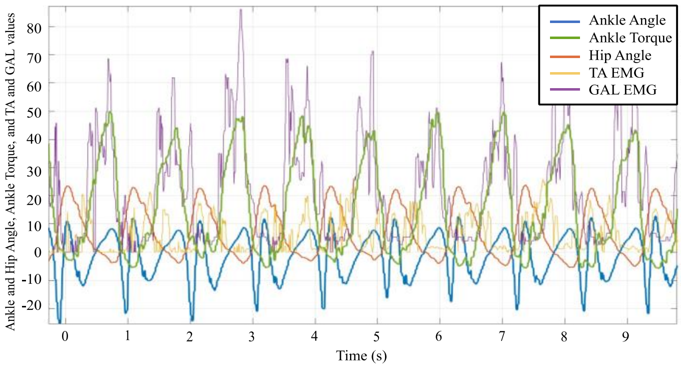

Fig. 4. Ankle and hip joint angles (in degrees, InertialLab), EMG data (as a percentage of MVC) from TA and GAL (Delsys), and ankle joint torque (in N.m) estimated in the SmartOs system, using a CNN with 2 convolutional layers.

4 Discussion

This study was developed in the context of robotics gait rehabilitation, where EMG-based control strategies are required to provide the patient with assistive training without imposing healthy joint motion. The primary contributions to the state of the art focused on proposing a tool to estimate ankle joint torque during walking motion without relying on (i) complex mathematical models that take too long to provide usable torques for exoskeleton control; (ii) force platforms that are limited to motion analysis labs; (iii) torque sensors, commonly not used in robotic assistive devices given their obtrusive design; and (iv) muscle-specific parameters that are difficult to measure.

This study demonstrates the proof-of-concept for using DL regressors to achieve a generalized estimation of ankle joint torque. The applicability of these regressors was tested under two slow walking speeds, namely 1.5 and 2.0 km/h, and for subjects with varying body height (from 1.50 to 1.90 m) and mass (from 50.0 to 90.0 kg). Consequently, this method enables the estimation of ankle joint torque covering the mean anthropometric data across countries. In addition, this work extends study [17], by optimizing the performance and the prediction time of a DL tool for ankle joint torque estimation, implementing it in a robotic assistive device for real-time operation.

The achieved results indicate that the hypothesis of estimating ankle joint torques based on EMG, anthropometric, demographic, and speed data is not supported, since better results were achieved when kinematic data were also included. In fact, these results are in line with the ones reported by [28]. Furthermore, the results show that CNN fed by EMG from TA and GAL, anthropometric information (body height and mass, shank and foot length), and hip kinematics (hip joint angles, angular velocities, and angular acceleration in the sagittal plane) along with the gender, age, and walking speed provided reasonably ankle joint torque curves (RMSE = 23.4±8.36 N.m, NMSE = 0.494±0.299, and SC = 0.754±0.105 in an effective time (2 ms). Study [7] predicted the isokinetic torques for the knee joint, achieving RMSE values between 26.8 and 29.0. Our study estimates the ankle joint torque for the entire gait cycle with lower RMSE values (23.4±8.36 N.m). In [8], the peak ankle joint dorsiflexion torque using linear and quadratic equations achieves a Correlation Coefficient (R) of 0.69. In our study, the best model presented a R value of 0.86±0.23 for the entire gait cycle. Moreover, the study [5] required 63 ms to estimate the knee joint torque using a musculoskeletal model. Our approach based on a DL model was able to estimate joint torque in 2 ms. The achieved outcomes proved that the proposed tool can be implemented in a robotic assistive device (in this case, SmartOs) with a low computational burden, which enable its use to control the ankle orthosis in real-time.

Despite the proposed DL tool offering promising results, there is still room for improvements, namely, (i) validate the CNN performance in SmartOs system with more participants, comparing the achieved results with ground truth data measured by force platforms; (ii) explore knowledge distillation methods to CNN model with more layers to reduce their computational burden.

5 Conclusions

This study addresses a gap in the current literature by introducing a DL-based model for estimating ankle joint torque trajectories in real-time. The hypothesis of estimating ankle joint torque trajectories without relying on kinematic information is not supported since the best DL model consists of a CNN with two convolutional layers, using as inputs EMG data from the TA and GAL muscles, hip joint kinematics in the sagittal plane (angle, angular velocity, angular acceleration), demographic (gender and age), anthropometric (shank and foot lengths, body height and mass), and speed data. This comprehensive model showed remarkable results with low computational burden in estimating ankle joint torque trajectories into a wearable CCU within 2 ms. Future studies can use this time-effective model for real-time ankle torque estimation, considering walking speeds ranging from 1.5 to 2.0 km/h and subjects with heights and masses varying from 1.50 to 1.90 m and from 50.0 to 90.0 kg, respectively.

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