Machine-Learning-Based Prediction of Gait Events From EMG in Cerebral Palsy Children

Christian Morbidoni, Alessandro Cucchiarelli, Valentina Agostini, *Member, IEEE*, Marco Knaflitz, *Member, IEEE*, Sandro Fioretti, and Francesco Di Nardo

***Abstract*— Machine-learning techniques are suitably employed for gait-event prediction from only surface electromyographic (sEMG) signals in control subjects during walking. Nevertheless, a reference approach is not available in cerebral-palsy hemiplegic children, likely due to the large variability of foot-floor contacts. This study is designed to investigate a machine-learning-based approach, specifically developed to binary classify gait events and to predict heel-strike (HS) and toe-off (TO) timing from sEMG signals in hemiplegic-child walking. To this objective, sEMG signals are acquired from five hemiplegic-leg muscles in nearly 2500 strides from 20 hemiplegic children, acknowledged as Winters' group 1 and 2. sEMG signals, segmented in overlapping windows of 600 samples (pace = 5 samples), are used to train a multi-layer perceptron model. Intra-subject and inter-subject experimental settings are tested. The best-performing intra-subject approach is able to provide in the hemiplegic population a mean classification accuracy (±SD) of 0.97±0.01 and a suitable prediction of HS and TO events, in terms of average mean absolute error (MAE, 14.8±3.2 ms for HS and 17.6±4.2 ms for TO) and F1-score (0.95±0.03 for HS and 0.92±0.07 for TO). These results outperform previous sEMG-based attempts in cerebral-palsy populations and are comparable with outcomes achieved by reference approaches in control populations. In conclusion, the findings of the study prove the feasibility of neural networks in predicting the two main gait events using surface EMG signals, also in condition of high variability of the signal to predict as in hemiplegic cerebral palsy.**

***Index Terms*— Cerebral palsy, children, gait-phase classification, machine learning, neural networks, surface EMG.**

I. Introduction

Cerebral palsy is the most common motor disability in childhood [1]. Pediatric hemiplegia is a form of unilateral cerebral palsy. It may cause altered selective motor control, weakness, stiffness of the limbs, and consequent balance and walking difficulties [2]. Clinical gait analysis (CGA) is the main tool to supply different indexes and parameters, suitable to quantitatively characterize human locomotion and to stress possible impairments of motor function. CGA is used to play a relevant part in clinical decision-making when managing child hemiplegia. Typically, CGA is able to provide four types of different data: spatial-temporal parameters, kinematics data, kinetics data, and electromyographic (EMG) signals. Many recent CGA studies focused particularly on the acquisition of surface electromyographic (sEMG) signals in cerebral-palsy children [3]–[8], probably due to the increasing availability of solutions based on it. The assessment of muscular recruitment by means myoelectric-signal analysis is, indeed, strongly advised in hemiplegic cerebral palsy, due to the neuromuscular involvement of this disorder [6].

During walking, sEMG signal needs to be synchronized with at least one other gait signal, in order to temporally characterize the muscular recruitment. The identification of the time when stride begins (heel strike, HS) and/or the transition time between stance and swing phases (toe-off, TO) is usually achieved by means of additional systems or sensors, such as cameras, foot-switch sensors, pressure sensing mats, and inertial measurement units (IMU). In order to prevent this, attempts were proposed to assess gait events by an artificial-intelligence-based interpretation of only sEMG signals. The adoption of sEMG-based approaches seems to be particularly suitable for studies focusing on exoskeletons. It was observed, indeed, that exoskeletons could benefit from the use of sEMG for gait-event detection in various ways, including the simultaneous control of assistance timing and intensity [9]. EMG signals are directly related to motion intention, thus being less sensitive than force sensors to ambiguity derived from contact with the environment, and potentially allowing to detect movement in advance, possibly reducing delays in control. EMG potentials in movement intent detection is also confirmed in [10], where EMG-based approach is reported to be able to detect gait initiation in transfemoral amputees earlier (63 - 138 ms) than inertial sensors. In [11], two groups of patients adopted the same powered ankle-foot orthosis, but relied on different control schemes: myoelectric controlled and footswitch controlled ones. Results showed that the first one leads to better gait patterns and lower muscle activation levels. Same findings are confirmed by more recent studies [12]. Finally, in [13] it was observed that EMG-based techniques are more robust to gait-event detection errors, showing better error recovery ability.

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by a Local Ethical Committee and performed in line with the Helsinki Declaration.

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Nevertheless, literature reports just a few studies [14]–[19], trying to face the problem of gait-event detection by means of machine-learning-based methods (see Section II, Related Works, for details). To our knowledge, a recent intra-subject approach, introduced by the present group of researchers, is still reporting the best performance among the EMG-based ones proposed in literature, showing a mean absolute error (MAE) of 14.4±4.7 ms and 23.7±11.3 ms in predicting HS and TO timing, respectively [19]. These encouraging performances were achieved considering data acquired during able-bodied-subject walking, where the clear majority of the strides (around 90%) follows the typical foot-floor-contact sequence, known as HFPS [20]: heel contact (0-6% of gait cycle, H), flat foot contact (6-38%, F), push-off (38-60%, P), and swing (60-100%, S). The possibility of extending the generality of these findings beyond control walking would be truly valuable, developing novel approaches able to detect and classify gait events from sEMG signal also in pathological condition, as pediatric hemiplegia.

Atypical stride, caused by drop foot or equinus deformity of the foot, is a frequent issue in ambulant children with spastic hemiplegia. The main atypical sequences are 1) PFPS: the first contact is with forefoot (P), then the heel landed on the ground (F), and standard P and swing (S) phases followed; and 2) PS: the first contact is again with forefoot (P), but it is followed immediately by swing phase (S), with the heel never getting to the floor. Recent studies showed that atypical cycles (PFPS and PS sequences) could characterize up to 85% of total strides in mild-hemiplegic children [3], [5]. In detail, it was reported that the initial contact with the ground of the hemiplegic foot is with the forefoot (PFPS and PS sequences) in 58% of total strides in mild-hemiplegic children [5], acknowledged as group 1 in the classification of spastic hemiplegia introduced by Winters *et al.* [21]. In Winters' group 2, PFPS cycles and PS cycles characterized 43% and 40% of total strides, respectively [3]. Predicting this large variability of foot-floor-contact sequences could be very challenging for automatic classifiers and the application of techniques developed specifically for walking of control subjects may not be enough. Thus, the goal of the present study is to investigate a machine-learning-based approach specifically developed to binary classify gait events and to predict HS and TO timing from sEMG signals in mild-hemiplegic-children walking. Depending on the application field, two main experimental settings are proposed: the intra-subject approach and the inter-subject approach [19]. In the first setting, sEMG data collected during walking of a single subject are used to train a neural network (NN) to recognize different gaits from the same individual. In the latter, gaits from a new individual are analyzed by a neural network trained on gaits from other individuals. In the present study, both approaches are tested. Numerous strides per subject (about 150, including only the hemiplegic-limb strides) are considered, in order to involve as much variability as possible.

II. Related Works

Gait partitioning and gait event detection are achieved in literature using different kind of sensors and resulting data [21]. While non-wearable sensors, as opto-electronic systems and force platforms, provide the best accuracy in indoor environments, wearable sensors are widely investigated as they are generally cheaper and enable a wide range of applications, e.g., prosthesis and exoskeleton control. Footswitches and foot-pressure insoles are considered as gold standard and often used as reference to evaluate the performances of proposed methods, based on other kind of sensors. In this section, the state of the art is reviewed, by first covering gait event detection approaches based on kinetic and kinematic data in section II-A, and then focusing on existing EMG-based approaches in section II-B.

A. Kinetic and Kinematic Based Approaches

1) Control Subjects: Several studies addressed gait event detection in healthy subjects by means of gyroscopes, accelerometers, and other kinematic sensors. In [22], seventeen different IMU-based algorithms are evaluated on a population of thirty-five healthy subjects and respective results, in terms of median time error (MED) and 25th–75th percentile error range (DMED), are compared. Reported results show a value of MED ranging from 60 to 65 ms and DMED from 40 to 111 ms for HS detection, while a MED from -25 to 6 ms and a DMED from 68 to 120 ms are observed for TO detection. The accelerometer-based method proposed in [23] has been evaluated on the MAREA dataset [24], including eleven healthy individuals walking on flat and inclined treadmill and on indoor flat ground. In this case, evaluation is measured by F1-score and Mean Absolute Error (MAE). F1-score is typically adopted to quantify the accuracy of model prediction on a dataset, based on the evaluation of true positives (correctly identify as positive), false positive (wrongly identified as positive), and false negatives (wrongly identified as negative). High F1-score values (> 0.90) indicate a good accuracy in prediction. Event predictions are accounted as correct (true positives) if they fall in a 61 ms interval from the ground truth event, and MAE is calculated on true positives only. Reported performances on treadmill walking are 0.99 F1-score and 16.4 ms MAE for HS detection, and 0.96 F1-score and 39.8 ms MAE for TO detection, while for indoor flat walking an F1-score of 0.99 and MAE of 17.8 ms are measured for HS detection and F1-score of 0.96, MAE of 27.0 ms for TO detection. In [25], a continuous-wavelet-transform-based feature extraction is performed for signals from tri-axial accelerometers and HS and TO instants are predicted. The algorithms were tested on eight healthy subjects walking on flat line and a ramp, a tolerance of 50 ms was used to individuate correctly matched event predictions (true positives), and a F1 score of 0.92 is obtained with the best system configuration (accelerometer positioned on the foot).

2) Patients Affected by Gait Disorders: Several recent works applied a neural network, called Long Short Time Memory (LSTM), to kinematic time series data for predicting gait events in children with gait disorders [26], [27]. In [26], a dataset composed of 9092 trials of children with different pathologies including cerebral palsy (the number of subjects is not specified) is used to train and evaluate an LSTM neural network. Inter-subject evaluation is performed. MAE is computed only for those trials where the number of predicted gait events equals the number of ground-truth events (99% of the trials form HS and 95% for TO). The average MAE reported is 18.3 ms for HS and 12.5 ms for TO. The study addresses real-time prediction, even if a peak detection algorithm, which makes use of potentially all the trial samples predictions, is applied to the output of LSTM network to identify gait-event timing. The granularity of the prediction is around 8.3 ms. In [27], data collected from 226 children with gait disorders are used to train and evaluate the performances of a bidirectional LSTM-based neural architecture. Inter-trial, but not inter-subject, evaluation is performed and the obtained MAE is 5.5 ms for HS and 10.7 ms for TO. In [28], a single IMU is adopted to train a thresholding algorithm with the aim of predicting HS and TO timing. The method is tested on five transfemoral amputee, resulting in an average error of around 2% of stride duration (computed from HS and TO estimates). In [29], two gyroscopes are used to detect seven gait sub-phases in children with cerebral palsy, reporting mean time error of 12.3 ms for HS and of 18.5 ms for TO.

B. EMG-Based Approaches

As discussed above, developing techniques to assess main gait events from only sEMG signals is of growing interest. Despite the potential advantages of EMG-based approaches, few efforts have been done in this direction, especially when subjects affected by neuro-motor disorders are concerned. In the following sections, the related state of the art is reviewed, focusing on control subjects and cerebral-palsy patients.

1) Control Subjects: Few works in literature address Machine-Learning-based classification of gait phases from only EMG signal. In [14], time-domain features have been extracted from EMG signal in order to classify stance and swing phases. Evaluation on treadmill walking of a single subject reported a maximum accuracy of 91.1%. Bilateral EMG features were used in [15] to train a support vector classifier. Intra-subject evaluation was performed on two subjects during walking on a treadmill at different speeds, reporting best accuracy of 96%. In [16], a control system for a foot-knee exoskeleton was proposed, based on the processing of eight EMG signals. Four time-domain features were extracted, and Bayesian Information Criteria (BIC) was used to predict eight gait events. Evaluation on one single healthy subject revealed low repeatability of the method, with a 30% drop in accuracy testing on different gait cycles. In [17], a set of temporal features were fed to a single-layer neural network to identify TO and HS timing on a population of eight healthy adults. The study targets inter-subject prediction by testing the network on one single unlearned subject (not used in training), however no cross validation is performed, and the test is performed on a 5-second trial only. No indication is provided regarding accuracy of prediction; a mean average error of 35 ms and 49 ms is reported for HS and TO prediction, respectively. The neural network used in this work is a simple single-layer network with 10 units and the Levenberg Marquardt algorithm was used to train the network. These methods are based on hand-crafted features; otherwise, previous studies by authors of the present paper adopted a featureless approach, employing Multi-Layer Perceptrons to process the envelope of sEMG signals [18], [19]. One further difference is the optimization algorithm: Leven berg Marquardt in [17], Adam in [18], [19]. Inter-subject evaluation on a population of twenty-three healthy adults reported overall mean classification accuracy (stance vs. swing) of 93.4%. A mean F1-score of 99.0% and a MAE of 21.6 ms were detected for the prediction of HS events and a mean F1-score of 98.4% and a MAE of 38.1 ms were identified for the prediction of TO events [18]. This approach has been numerically outperformed by a subsequent study of the same group of researchers based on intra-subjects experiments in the same population [19]. Average classification accuracy of 96.1±1.9% and mean MAE of 14.4±4.7 ms (associated to an F1-score of 99.3%) and 23.7±11.3 ms (associated to an F1-score of 98.5%) in predicting HS and TO timing were provided. To our knowledge, intra-subject approach is still reporting the best performance among EMG-based ones proposed in literature.

2) Patients Affected by Cerebral Palsy: As far as we know, only one research attempted to address machine-learning-based detection of gait events on cerebral-palsy children [30]. The algorithm presented in this study is based on ANFIS (Adaptive Neuro-Fuzzy Inference System), using percutaneous and sEMG signal and its first derivative as input and needs to be calibrated on each subject and re-calibrating each time it is used. Evaluation was made on eight subjects (8-18 years old) with diplegia and hemiplegia, ambulating with various degrees of assistance ranging from no assistance to walking with using an assistive device. Only the intra-subject prediction was assessed. The stereo-photogrammetric system (VICON motion analysis system) was used to assess foot-floor-contact signal, adopted as reference. The system was impossible to calibrate for one out of eight subjects and results are reported for the remaining seven subjects. Accuracy, simply computed as ratio between the number of predicted events and reference events, was around 0.97 and the reported mean prediction error was 30 ms. Large values of standard deviation were measured, confirming that the characterization of pathological gait is challenging.

III. Materials and Methods

A. Subjects

Foot-floor-contact and sEMG data during hemiplegic walking are taken from retrospective studies performed at Laboratory of Gait Analysis, Ospedale Santa Croce, Moncalieri (TO), Italy [3]. Two raters analyzed independently kinematic data and video-recordings from Lab database and pick up twenty school-age children with hemiplegic cerebral palsy. Ten children are acknowledged as Winters' group 1 and ten children as Winters' group 2. This classification of spastic hemiplegia was introduced by Winters *et al.* [21], based on sagittal joint kinematics. It considers four different classes (type 1, 2, 3, and 4), with a progressive distal-proximal involvement of the paretic lower limb. Types 1 and 2 are the mildest

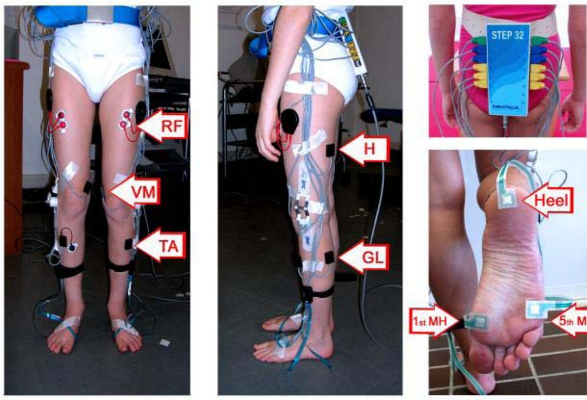

Fig. 1. Experimental set-up. GL is gastrocnemius lateralis, TA is tibialis anterior, VM is vastus medialis, RF is rectus femoris, and H is hamstring. Heel, 1st MH, and 5th MH mean that the footswitch is applied on the heel, 1st and 5th metatarsal head, respectively.

forms and the most observed in cerebral palsy. Type 1 is characterized by the occurrence of drop foot in swing, while type 2 by the equinism persistence all through the gait cycle, with a possible knee hyperextension during stance. These patient characteristics were stressed to further highlight the high variability of foot-floor-contact signal, expected among patients. Mean (±SD) children characteristics are: range: 5-15 years; 11 males/9 females; 10 right/10 left hemiplegia; mean age = 9.3±3.2 years; height = 131±18 cm; mass = 32.4±13.0 kg; Gross Motor Function Classification System level is between I and II. Children who underwent lower limb orthopedic surgery or botulinum toxin injections in six months preceding gait examination are kept out from the study. Informed consent is received from all subjects. The present research was undertaken following ethical principles of Helsinki Declaration and approved by local ethical committee.

B. Signal Acquisition

Foot-switch and sEMG signals are captured (sampling rate: 2 kHz; resolution: 12 bit) by the multichannel recording system Step32 (Medical Technology, Italy). 16 amplifier chains (one for each sensor) constitute the detection unit that collects signals coming from up to 16 different sensors. Each amplifier chain has its own sample-and-hold. The sample-and-hold circuits sample the 16 signals contemporarily, and then a single ADC converts the output of each S/H in sequence. Thus, digitally converted data correspond to analog signals collected at the same time instant.

sEMG signals are acquired by single differential probes placed in the hemiplegic limb over the five muscles mainly involved in walking task (Fig. 1): gastrocnemius lateralis (GL), tibialis anterior (TA), vastus medialis (VM), rectus femoris (RF), and hamstring (H). Winter's guidelines for sensor positioning were respected [31]. Sensor characteristics are: manufacture Ag-disks; diameter 4 mm; inter-electrode distance 12 mm; gain 1000; high-pass filter 10Hz, 2 poles. Foot-floor-contact signals are measured by three foot-switches affixed under: 1) the heel; 2) the first metatarsal head of the foot; and 3) the fifth metatarsal head of the foot (Fig. 1). Foot-switches characteristics are: activation force 3 N; dimension 10 × 10 mm; thickness 0.5 mm.

Each child walked barefoot, without using any assistive device, back and forth over a 10-m straight walkway for around 180 seconds. Cadence and speed were self-selected by each child. Possible crosstalk from surrounding muscles is inspected by visual inspection. Crosstalk is hypothesized when two muscles of the same anatomical region displayed concomitant activity with comparable amplitude modulation. To handle this issue, the procedure for reducing the possibility of crosstalk contamination with the use of Double Differential (DD) probes, instead of Single Differential (SD) ones, has been followed [32]. Specifically, double-differential sEMG sensors are adopted to further improve spatial selectivity. Sensor characteristics of these three-bar probes are: bar diameter 1 mm; bar length 10 mm; interelectrode distance 10 mm. Gain and filtering properties remain the same of single-differential ones. Single-differential and double-differential signals are then compared. When the amplitude of the double-differential signal is significantly lower, crosstalk is confirmed and the signal is rejected. In the present work, this happened in a very limited number of cases, not significantly undermining the numerosity of population.

C. Signal Pre-Processing

Foot-switch signals are processed for providing the segmentation of the foot-floor signal in the single gait cycles and then for identifying gait phases, following the acknowledged procedure introduced in [33]. Briefly, H-phase is identified when only the switch under the heel is closed. F-phase corresponds to the condition when the heel switch is closed, and at least one of the switches under the forefoot is closed too. P-phase is characterized by the condition when the switch under the heel is open, and at least one of the switches under the forefoot is closed. When all the switches are open, S-phase is acknowledged. HS is the first sample when only the switch under the heel is closed. TO is the first sample when both switches under the forefoot are simultaneously open. sEMG signals are band-pass filtered (linear-phase FIR filter, cut-off frequency: 20 - 450 Hz) for removing high-frequency noise and motion artefacts. The full-wave rectification of the filtered signal is performed. Afterward, linear envelope is computed by low-pass filtering the rectified signal (2^{nd}-order Butterworth filter, cut-off frequency 5 Hz).

D. Data Preparation

Data from the pathological leg only are included in the experiments. Signals are segmented in overlapping sliding windows (Fig. 2), where each window is shifted of a number of samples (pace) with respect to the preceding window. Each EMG-signal window is then labelled as stance (0) or swing (1) according to the value of the basographic signal corresponding to the samples in the detection window, in cases where these values are homogeneous (all values are 0 or all values are 1). In cases where basographic signal assumes different values within the detection window, the most frequent

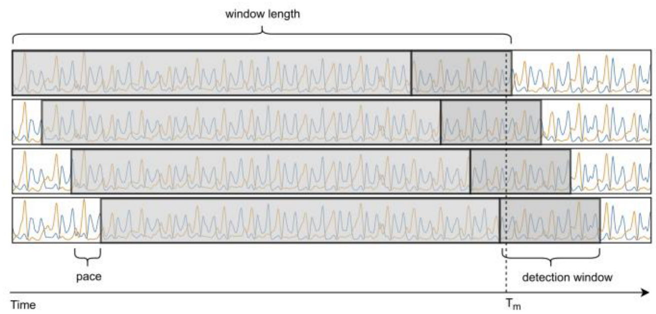

Fig. 2. Signal segmentation and labelling. Signals are segmented into overlapping sliding windows. Each window is then labelled according to the basographic signal corresponding to the last samples (the *detection window*). As shown in the case of T_m, each instant and the corresponding signal sample are included in multiple windows, thus providing multiple predictions for the same sample.

value is used to label the window. This could happen when the window covers a transition between stance and swing or vice versa. Illustrations of raw sEMG data from the five muscles and phase-transition timings from the basographic signal are reported in Fig. 3. The underlying idea is that the current state (gait phase), can be better predicted by looking at past segment of the signal, reflecting muscle activations that lead to that specific state. Foot-switch signal is used as ground-truth since force-based event detection is still considered as the reference method for assessing the accuracy of gait-event detection in different systems [34]. Moreover, foot-switches directly attached to the barefoot sole provide a direct measurement of foot-floor contact events and allow overcoming the limitation of collecting only a few gait cycles, typical of force plate and motion capture systems.

E. Tuning the Classifier

To choose a suitable gait phase classifier, preliminary experiments are performed, evaluating four different well-known Machine-Learning methods: Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Multi-Layer Perceptron (MLP). Dataset for such experiments is created, by adopting a pace of 100 samples and a detection window of 20 samples (10 ms). Different windows lengths are considered. A 5-fold evaluation is performed. In each fold, the training set is composed of the signal windows from sixteen patients, while the remaining four patients are used for testing. For each classifier, different parameters settings are tested. The resulting best settings are: SVM with linear kernel and C parameter set to 1, RF using 50 classifiers and maximum depth set to 10, KNN with K parameter set to 3. About MLP, the five models adopted in [18] are tested. They provided very comparable results, but the best ones are the single-layer model with 32 units (MLP1) and the three-layer model with 128, 64 and 32 units (MLP2). The average classification accuracy corresponding to different window lengths is reported in Fig. 4. The best results, almost identical, are achieved by MLP1 and MLP2, for all the tested window lengths. In particular, the higher accuracy corresponds to 600-sample (300 ms) window. Thus, this setting is adopted in the rest of the experiments. Apart from classification accuracy, MLPs are used in the full experiments as they provide faster predictions. Time to process a single 600-sample window under our experimental conditions is 0.25 ms for MLP1 and 0.55 ms for MLP2. Such a time rises up to 0.90 ms for RF and more than 1 s for SVM and KNN, making the latter two not suitable for real-time applications. Processing time is further debated in Discussion (Section C). In full experiments, described in detail in the following sections, window length is set to 600 samples, detection window is 20-sample long, and pace is set to 5 samples. In other words, the classifier is trained to predict the gait phase corresponding to a 20-sample interval (10 ms), based on EMG signals recorded during the previous 580 samples. The system uses sliding windows and outputs a prediction for each 2.5-ms segment, thus the prediction tolerance is 1.25 ms.

F. Training the Classifier

Two different experimental settings are addressed in the present study: the intra-subject (Fig. 5) and the inter-subject approach (Fig. 6). In the intra-subject setting, the gait signals for each subject are split into a training set (90%) and a testing set (10%). The process is then repeated, each time changing the testing set to cover the entire signal, following a 10-fold cross validation strategy. Thus, 20 different classifiers are trained, each one to learn the gait patterns of a single individual (i.e., 20 subjects = 20 classifiers). In the inter-subject setting, the training set is composed by gait signals of 19 subjects. The gait signal of the remaining subject is used as testing set. The process is repeated changing, at each time, the subject included in the testing set, following a 20-fold cross validation strategy. The goal of this experiment is to assess the capability of a neural classifier to predict the gait phases of an unseen subject based on the learned gait patterns from other previously-recorded subjects. As done in the preliminary experiments (Section III-E), different MLPs are evaluated, varying the number of layers and the units in each layer, as in [18]. In the intra-subject experiment, the best-performing model is MLP1 (single layer - 32 units), while in the inter-subject experiment the best-performing model results MLP2 (three layers - 128, 64, 32 units). To train the networks, the Adam optimization algorithm is adopted with a learning rate of 0.001 and a batch size of 32 data items. To decide the number of training epochs, we use an early stop technique, stopping the training if accuracy on the validation set (10% of the training set) does not increase for 10 consecutive epochs.

G. Gait-Event Identification

Once a trained model is available, the next step consists in employing it to detect the gait-event timing, that is to assess the instant when the transition between swing and stance, HS, (and vice versa, TO) occurs. To do so, for each fold, the EMG signals included in the testing set and segmented into sliding windows as described earlier are provided as input to the model previously trained on the corresponding training set. The model output was used to form the predicted

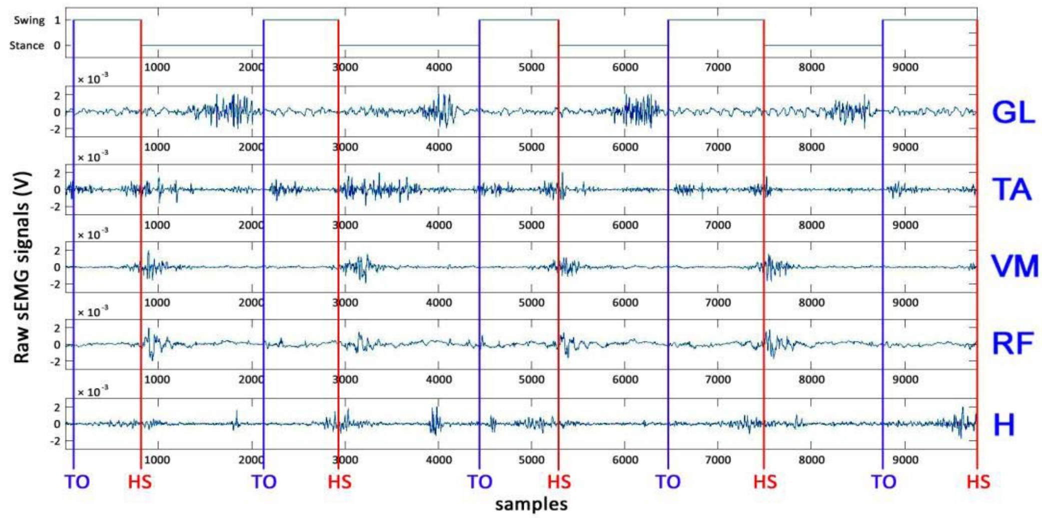

Fig. 3. Basographic signal (upper panel), raw sEMG data from the five muscles, and phase-transition timings from the basographic signals (HS and TO) from four strides of a representative hemiplegic children.

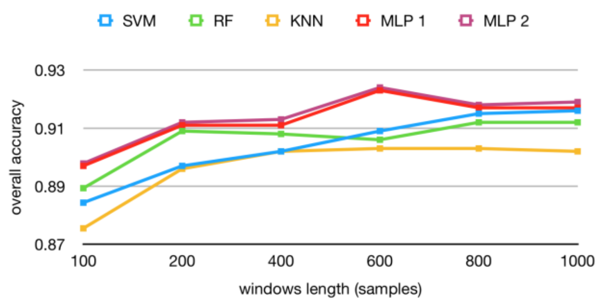

Fig. 4. Results of the preliminary experiments with different classifiers and different windows length.

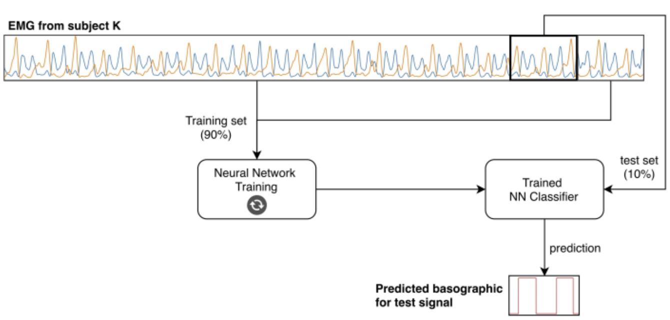

Fig. 5. Illustration of the experimental setting for the intra-subject approach.

basographic signal. As illustrated in Fig. 2 for the instant T_m, the model may produce multiple predictions for a single data sample, depending on window length, pace, and detection window setting. In this case, the predicted signal is built simply taking the more frequent predicted label. Following this procedure, the predicted basographic signal is achieved, made up of sequences of 0 (stance phase) alternating with sequences of 1 (swing phase). This signal is chronologically scanned to identify the transitions between gait phases: the transition from 0 to 1 identifies TO event and the following transition from 1 to 0 detects HS event.

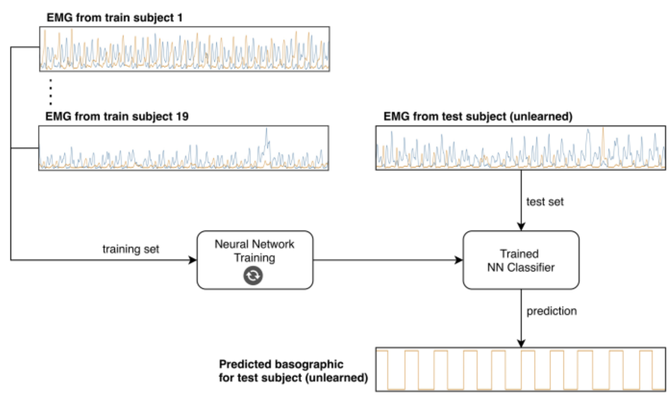

Fig. 6. Illustration of the experimental setting for the inter-subject approach.

Additionally, a post-processing procedure is performed to remove possible erroneously-predicted samples in the predicted basographic signal. It consists in cleaning the signal by identifying and then discarding those sequences of samples that are too brief to be physiologically plausible. Those sequences of samples are likely to be ascribed to classification errors and need to be removed. To do so, the following approach is adopted. Starting from the first HS, the next 300 samples (150 ms) are scanned to detect and remove those samples with a value = 1. Then, the next HS is identified, the procedure is performed again, and so on until the last HS event. Likewise, the first TO is identified and the next 300 samples are scanned to discard the samples with a value = 0. Then, successive TO is detected, procedure is run again, and so on until the last TO event. Finally, cleaned signal is scanned again in chronological order to identify the definitive HS and TO events.

H. Evaluation Strategy

To assess system performances, the following evaluation strategy is adopted. First, the signal-window classification task is evaluated measuring the overall classification accuracy. Next, the procedure used in the related literature is adopted [24], in order to evaluate the capability of predicting gait-event timing. Specifically, the first stage consists in setting a time tolerance T. Then, each predicted gait event (HS or TO) occurring at time tp has been marked as true positive when an event of the same type (HS or TO) occurs in the ground-truth signal at time tg, so that $|tg - tp| < T$. Otherwise, the predicted event is identified as false positive. Prediction accuracy is quantified by means of precision, recall and F1-score. Eventually, prediction error is quantified by means of mean average error (MAE) and time delay (TD). TD is computed as the relative value (with sign) of the same time distance. Signs "–" and "+" are adopted to indicate that the predicted event occurs earlier and later than the corresponding value in the ground-truth signal, respectively.

I. Validation

First of all, the performances of intra and inter-subject approaches are compared. The best-performing approach (the intra-subject one, as reported in "Results") is then validated by a direct comparison in the present population with a reference approach A recent machine-learning approach [19], introduced by the present group of researchers, is chosen as the reference, since it is still reporting the best performance in predicting gait events in control subjects, among the EMG-based approaches proposed in literature.

J. Statistics

Statistical difference of data distributions (accuracy, precision, recall, F1-score, and MAE) is evaluated. Firstly, Shapiro-Wilk test is adopted to appraise the normality of each data distribution. Next, two-tailed, non-paired Student's t-test is applied to verify the significance of the difference between normally-distributed samples. Likewise, Kruskal-Wallis test is applied to verify the significance of the difference between non-normally-distributed samples. Pearson's product-moment correlation coefficient and Spearman's rank correlation coefficient are adopted for computing correlation in normally and not normally distributed populations, respectively. Statistical significance is established at 5%.

IV. Results

Percentage of strides characterized by the different foot-floor-contact sequences is reported in Table I for each hemiplegic child, together with the total number of strides measured in the hemiplegic limb. Winters' group each subject belongs to is also indicated. Mean classification accuracies (± standard deviation, SD) achieved by the present approach over 20 folds in the testing set are 0.97±0.01 for intra-subject and 0.91±0.03 for inter-subject approach. A significant ($p = 0.70 \times 10^{-7}$) higher mean classification accuracy is detected in intra-subject approach. Average performances in identifying HS and TO timing in testing set are expressed in Table II by MAE, TD, precision, recall, and F1-score. No post-processing error correction was adopted in the computation of these performances. A 20% smaller mean MAE value is supplied by the intra-subject assessment of HS ($p = 0.01$), compared with inter-subject one. Likewise, a 22% smaller mean MAE is detected in TO prediction ($p = 0.004$). TD was computed to quantify the distribution of the assessment error between positive e negative values. Thus, statistical analysis was not performed on TD. Significantly higher values of F1-score are provided by the intra-subject approach for both HS ($p = 0.049$) and TO ($p = 0.015$). Detailed prediction errors for HS and TO are depicted in terms of MAE (Fig. 7) and TD (Fig. 8). Detailed prediction accuracy for HS and TO detection is reported in terms of precision, recall, and F1-score in supplementary material. An example of predictions of foot-floor-contact signal provided by intra-subject approach in a representative subject is shown in Fig. 9, considering strides with HFPS, PFPS, and PS sequences. As reported in Section III-I, the present intra-subject approach is validated by a comparison with a reference method [19]. Direct comparison of performances achieved with the two methods is shown in Table III. 40% reduction of mean MAE is reached by the intra-subject assessment of HS ($p = 5 \times 10^{-5}$), compared with reference approach (Table III).

TABLE I
PERCENTAGE OF FOOT-FLOOR-CONTACT SEQUENCES

subject	group	gait cycles	HFPS (%)	PFPS (%)	PS (%)	other (%)
1	1	134	78.4	14.9	3.0	3.7
2	1	120	75.8	17.5	0.8	5.8
3	1	129	0	1.6	0	98.4
4	1	136	0	94.9	0	5.1
5	1	150	0	90.0	0	10.0
6	1	118	14.4	67.8	0	17.8
7	1	114	4.4	48.2	36.8	10.5
8	1	167	53.3	32.9	0.6	13.2
9	1	93	75.3	17.2	0	7.5
10	1	119	89.1	7.6	0	3.4
11	2	110	0	78.2	19.1	2.7
12	2	152	0	57.9	5.9	36.2
13	2	167	0	0	99.4	0.6
14	2	173	0	79.2	3.5	17.3
15	2	130	0	12.3	78.5	9.2
16	2	77	0	10.4	89.6	0.0
17	2	93	0	76.3	8.6	15.1
18	2	99	11.1	74.7	3.0	11.1
19	2	85	0	67.1	4.7	28.2
20	2	89	1.1	75.3	22.5	1.1
Mean		123	20.1	46.2	18.8	14.9
±SD		29	32.9	33.1	31.9	21.7

TABLE II
MEAN PREDICTION PERFORMANCES

HS	MAE (ms)	TD (ms)	Precision	Recall	F1-score
intra	14.8±3.2*	-1.5±3.7	0.94±0.04	0.96±0.02*	0.95±0.03*
inter	18.3±4.6	5.2±10.6	0.88±0.17	0.91±0.16	0.89±0.16
TO	**MAE (ms)**	**TD (ms)**	**Precision**	**Recall**	**F1-score**
intra	17.6±4.2*	-2.4±4.0	0.91±0.07*	0.93±0.06*	0.92±0.07*
inter	22.5±5.6	0.4±14.3	0.81±0.14	0.84±0.13	0.82±0.14

* means that the considered parameter value is significantly different between intra-subject and inter-subject experiments.

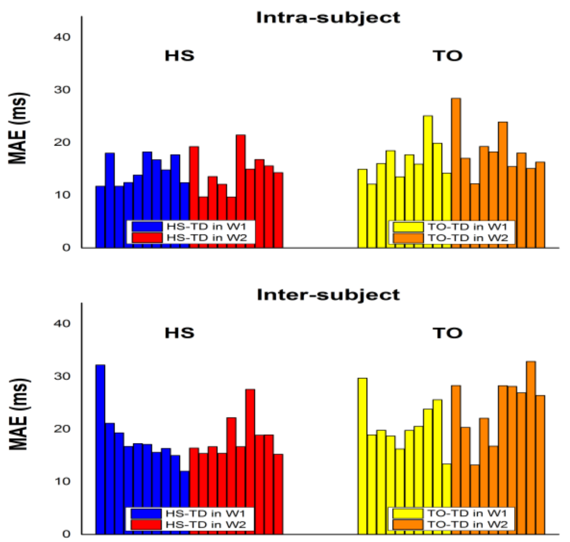

Fig. 7. Mean MAE computed in each subject for the intra-subject (upper panel) and inter-subject approaches (lower panel). Data are reported for HS with blue bars for W1 patients and red bars for W2 patients and for TO with yellow bars for W1 patients and orange bars for W2 patients.

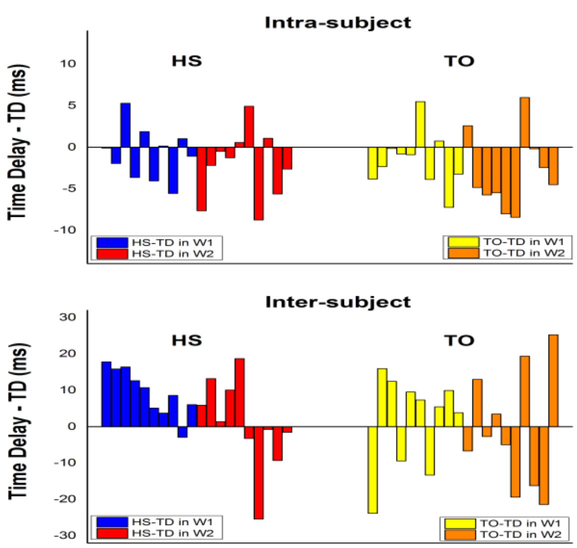

Fig. 8. Mean time delay (TD) computed in each subject for intra-subject (upper panel) and inter-subject approach (lower panel). Data are reported for HS with blue bars for W1 patients and red bars for W2 patients and for TO with yellow bars for W1vpatients and orange bars for W2 patients.

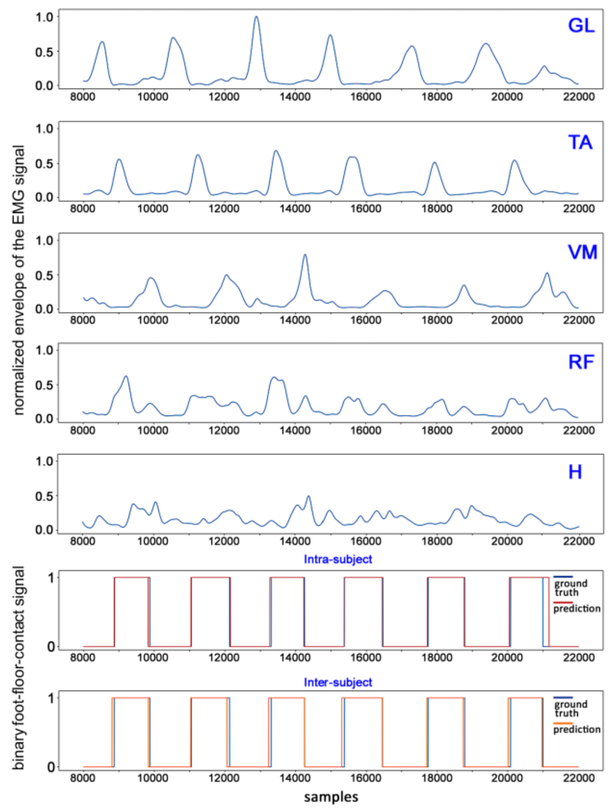

Fig. 9. Predictions of foot-floor-contact signal in the same six strides of a representative subject, provided by intra- and inter-subject experiments (two lower panels). Ground truth is depicted in blue. The five upper panels show the correspondent normalized full-wave rectified and enveloped signal in the five muscles of the hemiplegic leg, used as input to the neural network.

TABLE III
COMPARISON OF MEAN PREDICTION PERFORMANCES BETWEEN THE PRESENT AND THE REFERENCE APPROACHES

HS	MAE (ms)	Precision	Recall	F1-score
intra	14.8±3.2*	0.94±0.04*	0.96±0.02*	0.95±0.03*
reference	24.5±8.1	0.75±0.09	0.93±0.04	0.83±0.07
TO	**MAE (ms)**	**Precision**	**Recall**	**F1-score**
intra	17.6±4.2*	0.91±0.07*	0.93±0.06*	0.92±0.07*
reference	30.0±12.7	0.75±0.11	0.92± .09	0.82±0.09

* means that the considered parameter value is significantly different between present approach and reference approach.

Analogously, a 41% decrease of mean MAE is provided in TO prediction ($p = 3 \times 10^{-5}$). F1-score values are also significantly improved with the introduction of the intra-subject approach, for both HS ($p = 2\times10^{-9}$) and TO ($p = 4\times10^{-4}$). Correlation between prediction performances (MAE, precision, recall, and F1-score for both HS and TO) and the number of strides characterized by each foot-floor-contact (HFPS, PFPS, PS, and others, Table I) is also computed. For all tested data, correlation is not significant ($p > 0.05$). Effect of tolerance chosen to detect true positives on the quantification of the evaluation measures is shown in Tables IV-V. Results achieved using post-processing error correction (threshold 150 ms) are reported in Tables VI-VII.

V. DISCUSSION

The present work aims to provide a machine-learning-based detection of the two main gait events during hemiplegic-children walking, from only sEMG signals. sEMG-based prediction of HS and TO appears to be particularly significant and useful in walking condition where assistive devices are needed. It has been observed, indeed, that exoskeletons could benefit from adopting sEMG for gait-event assessment in different ways, including the simultaneous control of the timing and intensity of the assistance [9]. Main outcomes of the study lie in the fact that, despite the large variability of the

TABLE IV
AVERAGE PREDICTION PERFORMANCES ACHIEVED BY THE INTRA-SUBJECT APPROACH WITH DIFFERENT TOLERANCE VALUES (TOL)

HS	Tol (ms)	MAE (ms)	Precision	Recall	F1-score
	60	14.8±3.2	0.94±0.04	0.96±0.02	0.95±0.03
	150	16.6±4.0	0.97±0.02	0.99±0.01	0.98±0.01
	300	17.1±4.2	0.97±0.02	0.99±0.01	0.98±0.01
TO	**Tol (ms)**	**MAE (ms)**	**Precision**	**Recall**	**F1-score**
	60	17.6±4.2	0.91±0.07	0.93±0.06	0.92±0.07
	150	21.5±7.7	0.97±0.02	0.99±0.01	0.98±0.02
	300	22.2±8.1	0.97±0.02	0.99±0.01	0.98±0.01

TABLE V
AVERAGE PREDICTION PERFORMANCES ACHIEVED BY THE INTER-SUBJECT APPROACH WITH DIFFERENT TOLERANCE VALUES (TOL)

HS	Tol (ms)	MAE (ms)	Precision	Recall	F1-score
	60	18.3±4.6	0.88±0.17	0.91±0.16	0.89±0.16
	150	23.9±14.1	0.96±0.05	0.99±0.01	0.97±0.02
	300	24.7±14.6	0.96±0.04	1.00±0.01	0.98±0.02
TO	**Tol (ms)**	**MAE (ms)**	**Precision**	**Recall**	**F1-score**
	60	22.5±5.6	0.81±0.14	0.84±0.13	0.82±0.14
	150	33.0±13.2	0.95±0.05	0.99±0.01	0.98±0.03
	300	33.6±14.3	0.96±0.04	1.00±0.01	0.98±0.02

TABLE VI
EFFECT OF POST-PROCESSING ERROR CORRECTION: MEAN PREDICTION PERFORMANCES FOR INTRA-SUBJECT APPROACH AFTER CORRECTION*

HS	Tol (ms)	MAE (ms)	Precision	Recall	F1-score
	60	14.7±3.0	0.96±0.02	0.96±0.03	0.96±0.03
	150	16.6±4.1	0.99±0.01	0.99±0.01	0.99±0.01
	300	17.7±4.6	0.99±0.01	0.99±0.01	0.99±0.01
TO	**Tol (ms)**	**MAE (ms)**	**Precision**	**Recall**	**F1-score**
	60	17.6±4.1	0.93±0.07	0.93±0.07	0.93±0.07
	150	21.7±8.0	0.99±0.01	0.99±0.01	0.99±0.01
	300	22.7±8.4	0.99±0.01	0.99±0.01	0.99±0.01

*Treshold of 150 ms is used.

TABLE VII
EFFECT OF POST-PROCESSING ERROR CORRECTION: MEAN PREDICTION PERFORMANCES FOR INTER-SUBJECT APPROACH AFTER CORRECTION*

HS	Tol (ms)	MAE (ms)	Precision	Recall	F1-score
	60	18.3±4.6	0.91±0.16	0.91±0.16	0.91±0.16
	150	23.9±14.1	0.99±0.02	0.99±0.01	0.99±0.01
	300	24.9±15.6	1.00±0.01	1.00±0.01	1.00±0.01
TO	**Tol (ms)**	**MAE (ms)**	**Precision**	**Recall**	**F1-score**
	60	22.5±5.6	0.84±0.14	0.83±0.14	0.83±0.14
	150	32.0±13.1	0.99±0.02	0.98±0.02	0.98±0.02
	300	33.5±14.4	1.00±0.01	0.99±0.01	1.00±0.01

*Treshold of 150 ms is used.

signal to predict, the proposed approach is able to provide a suitable prediction of HS and TO which improves preceding sEMG-based attempts in cerebral-palsy populations [30] and is quantitatively comparable with outcomes achieved by reference approaches in control populations [19].

According with previous findings [3], three main foot-floor-contact sequences are detected in the present population of mild hemiplegic children: on average, HFPS sequence is found in 20.1±32.9% of total strides, PFPS sequence in 46.2±33.1%, and PS sequence in 18.8±31.9% (Table I). These percentages express a large variability of foot-floor contact across the population, associated to a just as big within-subject variability quantified by SDs. Each one of these foot-floor-contact sequences would correspond to a different sEMG pattern [3]. Thus, variability is expected not only in contact sequences but also in the associated sEMG signal. This variability is also enhanced by the fact that the walking task fulfilled by children involves deceleration, reversing, curves and acceleration, since they walked back and forth over a 10-m straight walkway for around 3 minutes. The large variability in both signals, compared to a healthy subject population, is expected to make the classification task more challenging. As a matter of fact, it is reasonable foreseeing reduced performances when both the input to the neural network (sEMG signal) and the signal to be predicted (foot-floor contact) are more variable, as in hemiplegic children.

A. Neural-Network Performances in Hemiplegic Population

Since a reference approach in hemiplegic-child walking is not available, the first stage of the present study is to test, on the present population of hemiplegic children, the EMG-based approach which is still reporting the best performance in predicting the two main gait events (HS and TO) in control subjects [19]. As aforementioned, this is an intra-subject approach based on a MLP interpretation of sEMG signals, proposed by the present group of researchers. In a population of 23 control adults, it achieves a MAE of 14.4±4.7 ms and 23.7±11.3 ms and a F1-score of 0.99±0.01 and 0.99±0.02 in predicting HS and TO timing, respectively [19]. Performances of this approach deteriorate when applied to the present hemiplegic-children population, in terms of both MAE (24.5±8.1 ms for HS and 30.0±12.7 ms for TO, Table III, reference line) and F1-score (0.83±0.07 for HS and 0.82±0.09 ms for TO, Table III, reference line). Deterioration was expected, but the size of this worsening is surprising (mean 48% increase in MAE and mean reduction of 0.17 in F1-score). This suggests that the approach which best performs in control subjects, could be not reliable in a different population.

Thus, the present study proposes an alternative approach, specifically developed to handle the large signal variability met in the hemiplegic population. The idea behind the setting described in Section III.D is that predicting the correct gait phase basing on a consistent number of previous signal samples could mitigate such a variability issue. This would allow the neural network to learn not only from local samples values (as in [19]), but also by analyzing the muscle-activation patterns that lead to a specific state. Beside that, the use of sliding overlapping windows increases the data used during the training phase. Mean classification accuracies and prediction performance are shown in Table II. Detailed prediction performances provided by this novel approach in each single subject are reported in Figures 7-8 and in supplementary material. Mean prediction performances over the hemiplegic population are compared with corresponding performances provided by the reference approach in the same population in Table III. The present approach clearly outperforms the reference one in terms of mean MAE, providing a 40% improvement for HS (14.8±3.2 ms vs. 24.5±8.1 ms, $p < 0.05$) and a 41% enhancement for TO (17.6±4.2 ms vs. 30.0±12.7 ms, $p < 0.05$). The same goes for F1-score in HS (0.95±0.03 vs. 0.83±0.07 $p < 0.05$) and TO (0.92±0.07 vs. 0.82±0.09, $p < 0.05$) assessment. The present approach seems to outperform also the performances of the only one other EMG study reported in literature, trying to address the issue of machine-learning-based assessment of gait events directly in child affected by cerebral palsy [30]. This ANFIS-based study reports the detailed prediction error for each gait event only in terms of TD: a mean TD of 4 ms (SD = 40 ms) for HS and –5 ms (SD = 31 ms) for TO prediction. The present approach can provide a mean TD of -1.5 ms (SD = 15.8 ms) for HS and –2.4 ms (SD = 18.4 ms) for TO prediction, showing a relevant reduction in both mean error values and SDs. Moreover, a mean MAE value over all predictions of less than 30 ms was achieved in [30] (detailed values are not reported) vs. the value of 14.8 ms and 17.6 ms produced by the present study for HS and TO, respectively. In [30], the reported mean prediction accuracy over gait events is around 0.97, simply calculated as the ratio between the number of predicted events and the number of reference events. In the present study, the prediction accuracy is evaluated by F1-score and, for the configuration with a 60-ms tolerance, is 0.95 for HS and 0.92 for TO prediction Considering the evaluation strategy (detailed in Section III.H), the quantification of the evaluation measures clearly depends on the tolerance chosen to detect the true positives: a bigger tolerance is related to a higher precision and recall and a lower MAE and TD. A tolerance of 60 ms is used in the present study, based on recent evaluation studies where such value is indicated as the maximum acceptable prediction error [22], [23]. Table IV shows as MAE and TD deteriorate when the tolerance increases from 60 ms to 150 ms, and further to 300 ms, while the prediction accuracy (precision, recall, and F1-score) improves. Nevertheless, MAE and TD values remain lower than those reported in [30] for every tolerance value in Table IV and F1-score values exceed 0.97 for tolerances > 60 ms. A further difference consists in the fact that in the present study foot-switch signal is adopted as the ground truth, since it represents the gold standard in gait segmentation [21], [32], [35], ANFIS study adopted the stereo-photogrammetry, introducing an uncertainty of 17 ms due to the video-frame resolution [30]. Otherwise, foot-switches fixed under the barefoot sole are placed in correspondence of precise easy-to-identify anatomical landmarks. This makes sensor positioning not particularly critical and provides a direct measurement of foot-floor contacts, supporting the use of foot-switches as a valid reference, ground-truth method. It needs to be mentioned that ANFIS study used only one sEMG sensor on each lower limb vs. the five sEMG sensors involved here. The use of a minimal set-up like that would help reducing the costs and simplifying the challenges associated with sEMG data acquisition in hemiplegic children. Besides these quantitative differences, it is worth to notice that the perspective is very different between ANFIS-based study and the present one. The present approach is designed for a general environment-independent prediction of gait events and could be suitable for different applications, as for example clinical gait analysis, smart prostheses, and EMG-driven assistive devices. Otherwise, ANFIS approach was developed for the specific long-term goal of assessing gait events to make up a controller for the application of functional electrical stimulation to leg muscles, to enhance walking capability. Thus, the need of calibrating the system for each subject to generate the ANFIS model (and re-calibrating each time it is used) could be acceptable for this specific aim, since the prediction of gait events occurs in real time, after model calibration. However, it is not suitable for the timing of everyday clinical application. In our intra-subject approach, the neural network should be trained with sEMG and basographic data for each new subject. The very good performances provided by this approach indicate that prediction of gait events of a single patient could be accurately achieved by processing data from only that specific patient. This outcome leads to argue that in the intra-subject approach, training could be performed only once for each patient. For all the successive tests, no further training and time consumption would be required. Although this seems to be a reasonable conclusion, sEMG data across separate sessions would be needed to support it. Thus, further studies will be designed to address this issue.

B. Intra-Subject Vs. Inter-Subject Approach

To try and overcome the aforementioned limitation, a so-called inter-subject approach was also tested on the same 20-hemiplegic-childred population. The inter-subject approach consists in training the neural network with sEMG signals measured during walking of a large population of patients and then testing the network on a population of brand-new patients affected by the same disorder. Thus, to run the inter-subject approach, a standardized dataset as larger as possible of foot-floor-contact and EMG signals from many different patients is needed to train the neural network [18], [19]. When such a dataset is available, prediction of gait events in new patients requires no further training and is no further time-consuming. Mean prediction performances provided by the inter-subject approach are displayed in Table II. A significant mean deterioration ($p < 0.05$) of 3.5 ms for HS-MAE and 4.9 ms for TO-MAE, respectively, associated to a significant mean worsening ($p < 0.05$) of F1-score (0.05 and 0.10 points), is observed for the inter-subject approach with respect to the intra-subject one. Although on average also the inter-subject approach appears to work adequately in terms of prediction error, a not negligible deterioration of prediction accuracy is the price to pay in adopting this approach. Ultimately, the present study proposes two different experimental approaches to the aim of predicting the two main gait events during hemiplegic-children walking: the intra-subject and the inter-subject approaches. As discussed, the intra-subject approach reports better quantitative performances for the present specific task, in terms of both prediction error (MAE and TD) and prediction accuracy (precision, recall, and F1-score). However, the adoption of the more appropriate approach should not be guided only by prediction performances but also by patient convenience and clinical requirement. In particular, the intra-subject approach seems to be more suitable for those situations where hemiplegic patients should undergo periodical tests and when high precision of the prediction is essential to correctly identify the small improvements of patient performances in temporal parameters during rehabilitation. In these cases, indeed, after a first session where basographic and sEMG must be acquired and the model trained, all the subsequent tests would not need neither to acquire basographic signal nor to train the model, but only to measure the sEMG signals of the single patient under examination. Conversely, the inter-subject approach is preferable when a large dataset from many subjects is available and when limiting time consumption is the priority.

To be noticed that most of the studies focusing on this topic involve data acquisition in the controlled conditions of treadmill walking [14]–[17]. The present study considers only walking on the ground without using any assistive device, in order to avoid mobility problems (i.e. fall risk) and gait-performance modification associated to treadmill walking [36]. Possible correlation between numerosity of each foot-floor-contact sequence and prediction performances is also tested. No significant correlation is detected ($p > 0.05$). This seems to suggest that the fact that hemiplegic walking affects the neural-network performances does not depend on the type of the single foot-floor-contact sequence, but on the large variability of sequences observed in this disorder.

C. Post-Processing and Computational Time

Experiments are performed on a machine equipped with a 2,6 GHz Intel Core i7 processor. The neural-network-processing time ranges from approximately 0.25 ms (for the one-layer network used in intra-subject setting) to approximately 0.55 ms (for the three-layer network used in inter-subject setting) for each EMG-signal window (composed of 600 samples for each muscle). As in our experimental setting, window-segmentation pace is 2.5 ms and four preliminary predictions are made for each data sample before a final prediction is produced. Temporal delay is between 10.25 and 10.55 ms. Although this paper does not explicitly target real-time applications, such a delay between the signal recording and the actual event detection could be acceptable under real-time constraints [26]. EMG-signal pre-processing does not further increase this delay, since envelope can be computed in real time [37]. Event-detection performances could be improved, by applying an error correction post-processing, at the cost of a longer delay of about 150 ms. As highlighted by the comparison between Tables VI and IV and between Tables VII and V, the effect of post-processing on mean MAE is negligible, in both intra and inter-subject approaches. Slight improvements are detected in terms of prediction-accuracy performances, mainly for the inter-subject approach (≈ 0.02 mean increase of F1-score).

VI. Conclusion

The outcomes of the present study prove the feasibility of neural networks in predicting the two main gait events using surface EMG signals, also in condition of high variability of the signal to predict as in mild cerebral-palsy hemiplegic children. Recurrent neural networks (RNN) are successfully used to interpret gait data (not sEMG), to detect gait event in healthy subjects. Future developments could test if involving RNNs may improve performances of the present approach. To the same aim, more advanced signal-processing techniques in frequency or time/frequency domain, such as wavelet transform, could be involved to provide further information to train the neural networks. From the clinical point of view, future efforts could be focused to generalize the present findings, including also more severe types of hemiplegia, such as Winters' type 3 and 4, or patients using assistive devices.

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