Real-time gait detection based on Hidden Markov Model: is it possible to avoid training procedure?

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***Abstract* — In this paper we present and validate a methodology to avoid the training procedure of a classifier based on an Hidden Markov Model (HMM) for a real-time gait recognition of two or four phases, implemented to control pediatric active orthoses of lower limb. The new methodology consists in the identification of a set of standardized parameters, obtained by a data set of angular velocities of healthy subjects age-matched. Sagittal angular velocities of lower limbs of ten typically developed children (TD) and ten children with hemiplegia (HC) were acquired by means of the tri-axial gyroscope embedded into Magnetic Inertial Measurement Units (MIMU). The actual sequence of gait phases was captured through a set of four foot switches. The experimental protocol consists in two walking tasks on a treadmill set at 1.0 and 1.5 km/h. We used the Goodness (G) as parameter, computed from Receiver Operating Characteristic (ROC) space, to compare the results obtained by the new methodology with the ones obtained by the subject-specific training of HMM via the Baum-Welch Algorithm. Paired-sample t-tests have shown no significant statistically differences between the two procedures when the gait phase detection was performed with the gyroscopes placed on the foot. Conversely, significant differences were found in data gathered by means of gyroscopes placed on shank. Actually, data relative to both groups presented G values in the range of good/optimum classifier (i.e. G ≤ 0.3), with better performance for the two-phase classifier model. In conclusion, the novel methodology here proposed guarantees the possibility to omit the off-line subject-specific training procedure for gait phase detection and it can be easily implemented in the control algorithm of active orthoses.**

***Keywords* — Hidden Markov Model, training procedure, active orthoses, IMUs system, real-time gait detection.**

List of Abbreviations

2P:	detection of 2 Phases
4P:	detection of 4 Phases
A:	Matrix of state transition
cHMM:	continuous Hidden Markov Model
FF:	Flat Foot
FSR:	Foot switches
G:	Goodness
HC:	Children with Hemiplegia
HO:	Heel Off
HS:	Heel Strike
L1:	Level walking at 1 km/h
L1.5:	Level walking at 1.5 km/h
ROC	Receiver Operating Characteristic
SPT:	Standardized Parameters Training
SST:	Subject-Specific Training
SW:	SWing
TNR:	True Negative Rate
TPR:	True Positive Rate
$\mathbf{w}_{jk}$:	Vector of mixture coefficient
$\boldsymbol{\mu}$:	Vector of mean values
$\boldsymbol{\pi}$:	Vector of initial state distribution
$\boldsymbol{\sigma}$:	Vector of standard deviations
^{ft}:	gyroscope place on FooT
$_{j}$:	j-th hidden state
$_{k}$:	k-th multivariate normal distributions
^{S}:	Standardized
^{sh}:	gyroscope placed on SHank
^{tr}:	trained

I. Introduction

Since the incidence increase of Cerebral Palsy (CP) in childhood [1], several studies in robot mediated therapy have been proposed in the last decades to reduce the effect of physical disabilities. In this prospective, the design of lower limb active orthoses achieved a relevant development to assist pathological gait [2]–[4]. In particular, it is possible to classify the lower limb wearable exoskeletons into two minor categories: ankle and knee orthoses. The first one is designed to provide assistance at the beginning of propulsion phase, also addressed as flat-foot, and to support the foot during swing

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phase to avoid the drop-foot [5], [6]; while the knee orthosis assists patient blocking the rotation of knee during flat-foot and allowing free motion during swing [7].

In order to ensure synchrony between the patients' intent and the assistance provided by the device, a real-time gait-phase detection is a fundamental step in the design of an effective control system [8], [9]. In the last years, several research groups have conducted studies on the sensors choice and/or algorithms to be implemented in the classifier, that are the core of the control system. Gyroscopes [9]–[11] and inertial measurement unit systems (IMUs) [12] are the mainly utilized sensors to detect gait-phases analyzing angular velocities with respect to other kinematic variables [10], for example linear acceleration. In the field of computational methodologies, Hidden Markov Model (HMM) have shown better performance [9], [11] with respect to other matching learning schemes [13].

A crucial and critical issue, related to the classification of gait phases with the use of matching learning schemes, is the training of the chosen classifier. The training phase permits the optimization of the model by adapting parameters to the experimental data in a recursive manner [14]. However, the training phase implies a relevant computational load and it has to be repeated for each patient prior to the current use of active orthoses.

In a larger research goal, we have developed the alpha-prototype of a Wearable Ankle-Knee Exoskeleton, addressed as WAKE-up! [15], for children with CP. Briefly, WAKE-up! is a modular lower limb unilateral active orthosis composed by an ankle module and a knee one, which can be used in a standalone scenario as well as coupled. The alpha-prototype uses, for the identification of the gait phases, angular velocities of foot and/or shank measured by gyroscopes and a reference sequence of gait phases provided by foot switches placed on the sole to train the classifier [9], [11].

Thus, considering the design constraint of real-time gait phase detection, the goal of this study is to identify a set of standardized model parameters to be applied in the HMM, avoiding the time consuming subject-specific training. We hypothesize that, by identifying a set of standardized model parameters from a data set of angular velocities of age-matched healthy subjects [16], it is possible to skip the training phase at the first use of active orthoses on the patient. In this way, it will possible to increase the usability of active orthoses and, by removing the foot switches, to simplify the sensorial system implemented in the WAKE-up!.

II. MATERIAL & METHODS

A. Theoretical Approach

We applied a decision rule based on scalar continuous Hidden Markov Model (cHMM) [9] for the gait-phase detection. In order to construct a cHMM, the number of hidden states, the probability distribution matrix of state transition (**A**) and the initial state vector distribution ($\boldsymbol{\pi}$) have been chosen. In particular, we examined two types of cHMM, varying the number of hidden states. Firstly, we selected four phases: Flat Foot (FF), Heel Off (HO), Swing (SW), and Heel Strike (HS), as the hidden states of cHMM. Secondly, we simplified the state by analyzing only FF and SW. In both models, **A** is chosen as a left-right model, while $\boldsymbol{\pi}$ is chosen giving the same probability to all states, since the initial state of model is unknown. Both the previously mentioned choices are identical to the ones already examined in Taborri *et al.*[9]. The cHMM analysis consists in two procedures: training and test. The first one was conducted by applying Baum-Welch algorithm assumed as the gold standard [14], while the latter by using an only forward algorithm [11]. Outputs of training procedure were:

- The trained probability distribution matrix of state transition $\mathbf{A}^{tr}$;
- The trained vector of mean values $\boldsymbol{\mu}^{tr}$;
- The trained vector of standard deviations $\boldsymbol{\sigma}^{tr}$;
- The trained vector of mixture coefficient $\mathbf{w}_{jk}{}^{tr}$;

where $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ indicate the mean and the standard deviation of the signal used as input of cHMM. The mixture coefficient $\mathbf{w}_{jk}$, for each hidden state j and for k multivariate normal distributions, is the weight used to extract the estimate sequence of states. The outputs of test procedure were the most likely sequence of states.

For more details on the HMM theory see Refs. [9], [14].

B. Experimental procedure

The experimental protocol involved twenty participants, divided into two groups: a control group with 10 typically developed children (TD, 9.5 ± 2.0 years) and an experimental group with 10 children with hemiplegia (HC, 7.8 ± 2.8 years). The inclusion criteria for TD was no known pathologies affecting walking pattern, while for HC was the ability to perform a walking trial without devices assistance. The protocol was approved by the Ethics and Medical Board of the Children's Hospital "Bambino Gesù", Rome, Italy. The procedure was explained to the parents' participants, oral informed consent was obtained from children and written consent was obtained from their parents.

Angular velocities, in the sagittal plane, of participants' foot and shank were acquired by means of gyroscopes embedded in two MIMUs (XBus Master MTx, Xsens Technologies, The Netherlands). Moreover, to extract a reference sequence of gait phases, the contact between foot and ground was recorded by four foot switches FSRs (Wave, Cometa, Italy); they were positioned on heel, toe, first and fifth metatarsophalangeal articulations. In particular, TD were equipped only on the right lower limb, while HC only on the more affected limb.

Protocol was composed of two walking tasks on a treadmill with inclination 0% (level walking) for at least 60 seconds at two speeds, respectively 1.0 (L1) and 1.5 km/h (L1.5). The full set of tasks was completed by all participants. All tasks were repeated two times. Instrumentation phase and walking tasks were finished in about half an hour: TD did not express fatigue, while HC rested between each task.

C. Data processing

Unfiltered data were acquired at 200 Hz from the FSRs and 50 Hz from the MIMUs; the gyroscope data were further interpolated to match the FSR acquisition rate.

All data were analyzed off-line by using MATLAB software (2012b, MathWorks, USA). The first step of the data processing consisted in the gait partitioning by means of the FSRs output. In Tab. I the logic of partition, based on pressed foot switches, is shown respectively for the case of four phase model (4P) and two phases model (2P). The FSR outputs were used as a reference for the two scalar cHMM [9], [11].

TABLE I. LOGIC OF PARTITIONING FOR FOUR PHASES AND TWO PHASE. X INDICATES THAT FSRS ARE PRESSED AT THE SAME TIME,* THAT AT LEAST ONE OF FOUR FSRS ARE PRESSED.

	Four Phases 4P				**Two Phases 2P**	
	FF	HO	SW	HS	FF	SW
Heel	x			x	*	
Toe	x	x				
1st Metatarsus	x	x				
5th Metatarsus	x	x				

The output of gyroscopes was filtered with a low-pass Butterworth with 15 Hz cut-off frequency; then was partitioned into the gait phases by means of the foot switch data. After the normalization of the time length of each phase, mean and standard deviation of the angular velocities were calculated.

Two approaches were used to perform the training phase. In the first approach, identical for TD and HC groups, the first trial was used to train cHMM and the second one to test it with an "only forward" algorithm [9], [11]. We addressed this type of training as Subject-Specific Training (SST).

In the second approach, we introduce a novel methodology, addressed as Standardized Parameters Training (SPT), for which the validation method was specialized for TD and HC groups. Actually, as regards the TD group, a leave-one-out cross validation analysis was applied, using the average of the gyroscope outputs of the first trial of nine subjects to train cHMM. Then, the second trial of the remaining one was used for the validation. The procedure was repeated in a recursive manner, leaving one subject for validation in turn. Instead, as concerns HC group, a cross-validation was applied using the average of the gyroscope outputs of the first trial of all subjects of TD group to train cHMM. Then, the second trial of each subject in HC group was tested with "only forward" algorithm. The SPT permits the evaluation of: $\mathbf{A}^S$, $\boldsymbol{\mu}^S$, $\boldsymbol{\sigma}^S$ and $\mathbf{w}_{jk}{}^S$, where S means standardized.

Both procedures, SST and SPT, were replicated: (i) on foot gyroscope outputs and on shank gyroscope outputs; and (ii) for the 4P and 2P models.

D. Data analysis

Since we used two sensors (gyroscope placed on the foot, ft, and the shank, sh), two models of gait discrimination (four phases, 4P, and two phases, 2P), and two types of training (Subject-Specific Training, SST, and Standardized Parameters Training, SPT), a cluster of eight classifiers was obtained for each of the twenty subjects and for the two tasks (L1 and L1.5), addressed as: $SST^{ft}_{4P}, SPT^{ft}_{4P}, SST^{ft}_{2P}, SPT^{ft}_{2P}, SST^{sh}_{4P}, SPT^{sh}_{4P}, SST^{sh}_{2P}$ and SPT^{sh}_{2P}.

We choose two statistical parameters to evaluate the performance of the eight classifiers, in particular True Positive Rate (TPR) or sensitivity, and True Negative Rate (TNR) or specificity. Both parameters TPR and TNR were calculated by using FSR signals as reference and with a tolerance window of 60 ms centered at each time step [9], [11]. In particular, the similar transition detected by FSRs and estimated by cHMM was considered as true positive, while the similar non-transition as true negative. By means of TPR and the complement of TNR, we performed a Receiver Operating Characteristic (ROC) curve analysis [17].

In order to evaluate the overall capability of a classifier to individuate correctly gait phases both in terms of transitions and in terms of non-transitions, we computed the Goodness (G) of the each classifier from ROC space. Similar to the approach of Perkins and colleagues to individuate the optimal cut-off of classifier [18], G was evaluated as the complement of Youdness parameter, see Eq.1. Thus, for each classifier, G represents the Euclidean distance between the evaluated point in the ROC space and the point [0 1], which represents the optimum classifier in the ROC space.

$$G = \sqrt{(1 - TPR)^2 + (1 - TNR)^2} \qquad (1)$$

G can assume values between 0 and $\sqrt{2}$, and a classifier can be considered: (i) optimum when $G \leq 0.25$; (ii) good when $0.25 < G \leq 0.7$; (iii) random if $G > 0.7$ [17]. Finally, for each classifier mean and standard deviation of G were calculated.

G data were tested for normality with the Shapiro-Wilk test. Then, paired-sample t-tests were applied on G values, in order to find significant differences between the two types of training procedures SST and SPT. Statistical significance was set at 0.05. Since the effectiveness of active orthoses, as WAKE-up!, depends on the simultaneous correct discrimination of transitions and non-transitions between gait phases, we decided to conduct the statistical analysis on G data, and not separately on TPR and TNR. The software package SPSS (IBM-SPSS Inc., USA) was used.

III. RESULTS AND DISCUSSIONS

The values of Goodness were reported in Fig.1. From an exam of this figure it emerges that all classifiers achieved an optimum G value ($0.08 \leq G \leq 0.25$), with the exception of the ones applied on shank angular velocity in HC group for the discrimination of four phases (SST^{sh}_{4P} and SPT^{sh}_{4P}), which assumed a value in the range of good classifiers ($G \approx 0.3$). The standard deviations were always ≤ 0.1 in the TD group and always ≤ 0.2 in HC group. The greater values of standard deviations in HC group indicate, as expected, an angular velocity waveform with a greater variability among patients with neuromotor disorders.

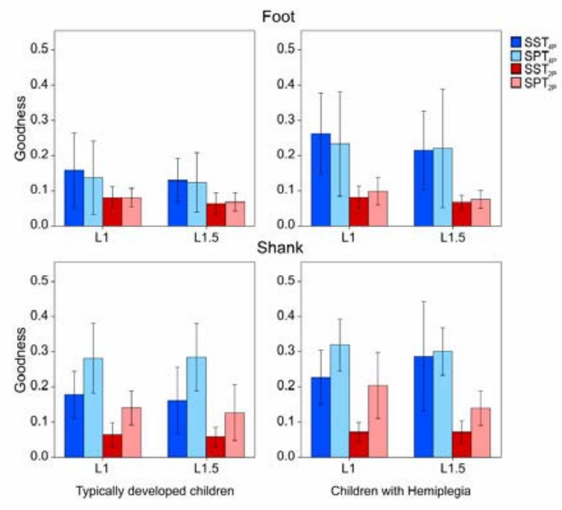

Fig.1 Goodness for typically developed children TD and children with hemiplegia HC, in both trials (L1, L1.5), for foot and shank, for the two training procedures (SST and SPT) and for the two types of gait discrimination (4P and 2P).

As concerns the qualitative comparison of the mean G values reported in Fig.1 for 4P and 2P, classifiers showed better performance when the recognition of two phases is required. In particular, for both body segments, G achieved in 2P values lower of 0.08 with respect to 4P. This finding confirmed the expectation that the discrimination of two phases is easier than the discrimination of four phases. Actually, the similar pattern in the signal shape of sagittal angular velocity in HS and FF causes an increase of incorrect gait-phase classification and, consequently, an increase in G values. As reported in the Introduction section, the knee module of the WAKE-up! is conceived to give assistance to patient only at the start of FF and at the start of SW. Thus, for the knee module the recognition of HS and HO is redundant and our findings can be useful in order to implement a classifier for the control system of knee module with a consequent decrease of computational load.

As regards the two tasks L1 and L1.5, better qualitative results of G (lower than 0.03) are achieved with the second task (L1.5) with respect to first one (L1). Evidently, the increase of walk velocity with an equal time length of the task implies an increase in the number of gait cycles gathered and then, more information are available to train the classifier. Furthermore, amplitude of angular velocity waveform increases with the increase of velocity, thus, the different patterns of the waveform between the gait phases are more distinguishable.

Moreover, from a comparative exam of the application of cHMM, for foot and shank, in healthy adults [9] with the here discussed results obtained with healthy children and children with cerebral palsy, it emerges that SST^{ft} and SST^{sh} do not exhibit relevant differences (in average G $\leq$ 0.03). We comment this finding reporting the results of Hausdorff *et al.* [19], in which the Authors discussed the maturation of gait dynamics and affirmed that children ankle reaches a complete maturation in terms of gait control approximately at 11 years. In the prospective of the control implementation of the WAKE-up! for pediatric use, this finding implies that the gyroscope on the foot is not necessary for an effective gait recognition. In the SPT procedure, SPT^{sh}_{4P} and SPT^{sh}_{2P} achieved worse results in terms of Goodness (< 0.12) with respect to SPT^{ft}_{4P} and SPT^{ft}_{2P}. Such a result indicates that the peak-to-peak variation observed during gait phases of foot angular velocity waveform provides a better set of standardized parameters to train the classifiers.

Taking into account only the two procedures of training SST and SPT as independent variables, the results of paired-sample t-test are shown in Tab. II.

TABLE II. P-VALUE OF PAIRED T-TEST BETWEEN TWO TYPES OF TRAINING PROCEDURES. STATISTICAL SIGNIFICANCE WAS SET AT 0.05.* INDICATES THE SIGNIFICANT DIFFERENCES FOUND.

	Typically developed children TD		**Children with Hemiplegia HC**	
	L1	**L1.5**	**L1**	**L1.5**
SST^{ft}_{4P} - SPT^{ft}_{4P}	0.66	0.88	0.62	0.92
SST^{ft}_{2P} - SPT^{ft}_{2P}	0.99	0.75	0.32	0.40
SST^{sh}_{4P} - SPT^{sh}_{4P}	0.02*	0.01*	0.02*	0.81
SST^{sh}_{2P} - SPT^{sh}_{2P}	0.001*	0.02*	0.0001*	0.001*

As regards the classifiers trained by angular velocity of foot, the results of statistical analysis indicate that for both groups (TD and HC) and both tasks (L1 and L1.5), SST and SPT exhibit no significant differences in terms of Goodness. While, as regard classifiers trained by shank data, only for level walking at 1.5 km/h and for HC group in the four phases model, the two types of training procedures do not show statistical differences. However, in the remaining cases, although paired-sample t-tests are significant, the classifiers trained with standardized parameters achieved good results in terms of Goodness. The significant differences found could be related to the observed data spread.

The previously indicated statistical findings suggest that it is possible to avoid the off-line subject-specific training phase of cHMM, when a set of standardized parameters is obtained from data gathered via an one-axis gyroscope placed on the foot.

Moreover, although statistical differences were found, G values allow the possibility to omit SST also with a set of standardized parameters obtained via an one-axis gyroscope placed on the shank. Actually, the performance in this case, even if worse than SST one, can be considered good enough to correctly control active orthoses.

IV. CONCLUSION

In this paper we presented a study on the viability of omitting the preliminary training procedure of a Hidden

Markov Model for real-time gait detection, useful to control lower limb active orthoses. The new procedure, addressed as Standardized Parameters Training, is based on the identification of a parameter set obtained by angular velocity data relative to age-matched healthy subjects. Our findings show that all here examined classifiers achieved a value of Goodness in the range of good/optimum classifiers in the ROC space ($G \leq 0.3$). Moreover, the here proposed method can successfully replace the more used Subject-Specific Training method, when the classifiers applied on foot angular velocity. As regards classifiers applied on the angular velocity of shank, significant differences were found between two training procedures. However, the performance reached by classifiers trained with the here proposed and validated method ensure the possibility to correctly control an active orthosis designed for pediatric use.

In conclusion, we report the better performance achieved by the classification of an only two gait phases model with respect to four phases one. This represents a relevant result since it allows the control of knee module of an active orthosis by a classifier able to recognize only flat foot and swing phases.

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