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Walking assistance using artificial primitives

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Abstract—Bio-inspiration in robotics deals with applying biological principles to the design of better performing devices. In this work, we propose a novel bio-inspired framework using motor primitives for locomotion assistance through a wearable cooperative exoskeleton. In particular, the use of motor primitives for assisting different locomotion modes (i.e., ground-level walking at several cadences and ascending and descending stairs) is explored by means of two different strategies. In the first strategy, identified motor primitives are combined through weights to directly produce the desired assistive torque profiles. In the second strategy, identified motor primitives are combined to serve as neural stimulations to a virtual model of the musculoskeletal system, which in turn produces the desired assistive torque profiles.

The paper further reports the results of an experiment conducted with healthy participants where the proposed strategies were tested for the first time with a wearable robotic exoskeleton for hip assistance. Several volunteers performed the task of ground-level walking in different conditions. These experimental activities highlighted the capacity of volunteers to naturally interact with the device and benefit from the assistance in terms of physical effort.

Index Terms—Bio-inspired, primitives, control, orthosis, exoskeleton.

I. BIO-INSPIRED LOCOMOTION ASSISTANCE

AGEING among populations is a critical challenge for industrialized countries. 40 years from now, nearly 21% of the European population will be older than 60 years old [1]. Therefore, it is urgent to develop new technologies that promote the establishment of an active and sustainable ageing society. Incidence of gait disorders and lower-limb impairments is higher among aged people and can reach 35% and 60% prevalence in persons over 70 and 80 years of age, respectively [2]. This scenario is expected to lead to an increasing number of people with *gait disturbances* (e.g., senile gait, gait post-stroke hemiparesis, lower-limb amputations) who may benefit from the use of lightweight, assistive wearable robots to recover a more stable, efficient, and autonomous locomotion [3][4].

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Several wearable robots for lower-limb movement assistance can be found in the literature. However, despite the tremendous work carried out by engineers, many challenges regarding the design of an effective physical and cognitive human-robot interface still remain.

In this framework, a compelling research topic is the development of an adaptive, robust, and intuitive control strategy to decode the intended movement of users with mild lower-limb impairment and smoothly provide them with coherent and collaborative assistance. An extensive review of such devices and their control strategies can be found in [5][6]. Hereafter, we recap the most relevant approaches and their major limitations.

Several authors explored the use of superficial electromyographic signals (EMGs) to generate assistive torques [7]. However, EMG-driven devices face the problem of deploying a complex and sensitive sensory apparatus and require advanced and computationally-greedy signal processing in order to filter out measurement noise and signal instability [8]. Furthermore, laborious tuning for each subject and even training session is needed.

In other seminal contributions, the estimate of the assistive torque was derived from the computation of a dynamic model of the exoskeleton or the exoskeleton-human complex [9]. This approach mostly suffers from the lack of accuracy of the model, the heavy computational load, and the need to deal with the identification of as many different dynamic models as the number of users.

A promising approach that has been recently introduced gets inspiration from the so-called central pattern generators (CPGs), i.e. neural oscillators located in the spinal cord of mammals. CPGs are considered as the *source of rhythmicity* in locomotion due to their capability of providing rhythmic excitation to the muscles, even if receiving non-periodic inputs [10][11]. Based on this idea, adaptive oscillators (AOs) were proposed as mathematical tools to extract the periodic characteristics of locomotion and therefore emulate the role of CPGs as neural oscillators. AOs are coupled to user movements so that they provide the necessary entrainment between the device and the user by delivering appropriate assistive patterns [3][12][13]. In some cases, AOs were used to adapt pre-recorded trajectories or torque profiles to the user gait pattern, which implied adding more profiles every time a new manoeuvre is programmed [3]. Other contributions explored the ability of AOs to synchronize with and learn the monitored gait pattern in order to enhance the user gait by means of virtual impedance fields [13]. Such approaches are prone to find difficulties while transitioning from one locomotion mode to another, e.g., changing from walking to ascending stairs.

In this work, we propose an innovative bio-inspired frame-

work that further exploits the concept of CPGs by combining AOs with artificial motor primitives for the development of a control strategy to assist locomotion through a wearable cooperative exoskeleton.

Physiologically speaking, motor primitives can be defined as a network of spinal neurons that forms one basic module that activates a determined set of muscles. In other words, they are a set of basic signals that are able to generate through proper recombination the large set of muscle stimulations needed for different locomotion tasks. The existence of these primitives has been widely studied and supported by contributions like [16][17]. In this work, Bizzi et al. reviewed the experiments establishing that 5 time-varying signals could explain the EMG recordings of 13 leg muscles in 3 intact frogs during swimming, jumping, and walking. Similarly, in humans, the work of [18] and [19] identified 5 to 6 basic components that could reconstruct all the measured EMG signals for several locomotion tasks, such as walking and running at different speeds. Though these studies mainly focused on EMG recordings, similar correlations of signals have been also found at other levels, i.e., neural, dynamic, and kinematic levels [17][20].

Such primitives present several potential advantages for motor control. First, inferring high-dimensional sets of data from a small set of simple signals provides an advantageous reduction in dimensionality [11]. Additionally, this reduced set of primitives also implies a simplification of the coordination, since a reduced number of control signals is used to trigger them with the appropriate combination. Moreover, this combination is done linearly, which provides an efficient way of bypassing the inherent non-linearities that govern movement control [11].

These advantages make the physiological concept of motor primitives an inspiring foundation for the control of artificial devices like orthosis, prosthesis, and even autonomous robots. These devices may benefit from a primitive-based control in complex environments where different locomotion modes are requested [21]. Furthermore, the use of the same reduced set of primitive signals for different locomotion tasks presents the desirable advantage of generating smoother transitions between them.

In this work, the generation of artificial primitives is studied at two different levels, namely, dynamic and neural levels. The controller based on dynamic level primitives combines a set of basic signals to directly generate desired torque profiles. In the case of the neural level, a further step towards bio-inspiration is taken, in the sense that primitives are combined to produce virtual muscle stimulations. Therefore, a musculoskeletal model is needed to turn these stimulations into desired joint torques. In both strategies, adaptive oscillators are used to continuously synchronize the primitives to the subject's instantaneous walking cadence, allowing for adaptation to the diverse gait frequencies and phases [22].

Section II describes the proposed control strategies based on motor primitives and how such primitives are obtained. In the following Section III and Section IV, we report materials and methods together with results of an experiment conducted with healthy participants where the proposed assistive strategies were tested with a wearable robotic exoskeleton for hip

assistance. Finally, Section V draws conclusions and prospects future research activities.

II. PRIMITIVE-BASED CONTROL

The proposed assistive strategy based on both dynamic-level and neural-level artificial motor primitives (*DLMP* and *NLMP*, respectively), is depicted in Figure 1.

Common blocks of both strategies include the following: (i) the intention detection, which monitors the subject's behaviour in order to select among the different locomotion modes, i.e., standing, walking, and ascending/descending stairs; and (ii) the adaptive oscillators, which are in charge of providing the gait frequency (cadence) and phase for each leg independently. These features are necessary in order to select the appropriate combination of primitives in a coordinated timing. On the other hand, both strategies differ as follows. In the case of the control strategy based on *DLMP* (Figure 1A), primitives are combined with different weights to generate the desired joint torque profiles for the hip, knee, and ankle. Otherwise, the control based on *NLMP* (Figure 1B), combines a different set of primitives to generate muscle stimulations. These stimulation signals enter a simplified musculoskeletal model comprising seven muscle-tendon units based on Hill-type muscles adapted from [14]. This model transforms the stimulations into muscle-tendon forces and finally projects them into joint torques. Therefore, the *NLMP*-based control is also dependent on the actual kinematics of the subjects, and it is thus adaptive to their natural gait pattern. With this bi-directional adaptation, the subject can better exploit the assistive potential by also adapting his/her gait to optimize the received assistance [15].

We computed both sets of motor primitives (*DLMP* and *NLMP*) for three locomotion tasks, namely, walking and ascending and descending stairs. With this aim, a database was constructed by collecting data from different references, providing kinematics and dynamics in the sagittal plane of walking at different cadences and ascending and descending stairs (see Table I). These contributions provide a single set of signals for both legs, assuming a symmetrical gait in healthy subjects.

In order to simplify the primitive extraction process, stairs data were averaged and walking signals were grouped and averaged in five bins of walking cadences, i.e., [0.6-0.69], [0.7-0.79], [0.8-0.89], [0.9-0.99], and [1.0-1.09] cycles/s. These signals were further normalized with respect to time as the percentage of gait cycle (0-100% with 0% being coincident with the corresponding leg heel strike). Computations were performed using custom software routines (Matlab R2013a, The MathWorks Inc, Natick, MA, USA).

Then, the primitives were extracted with techniques such as non-negative matrix factorization (NNMF) or principal component analysis (PCA). Both of these techniques extract a linear combination of primitives C and the corresponding weights W in order to minimize the difference between the original signals and the reconstructed ones S :

$$S_{e,t} = W_{e,n} \cdot C_{n,t} \quad (1)$$

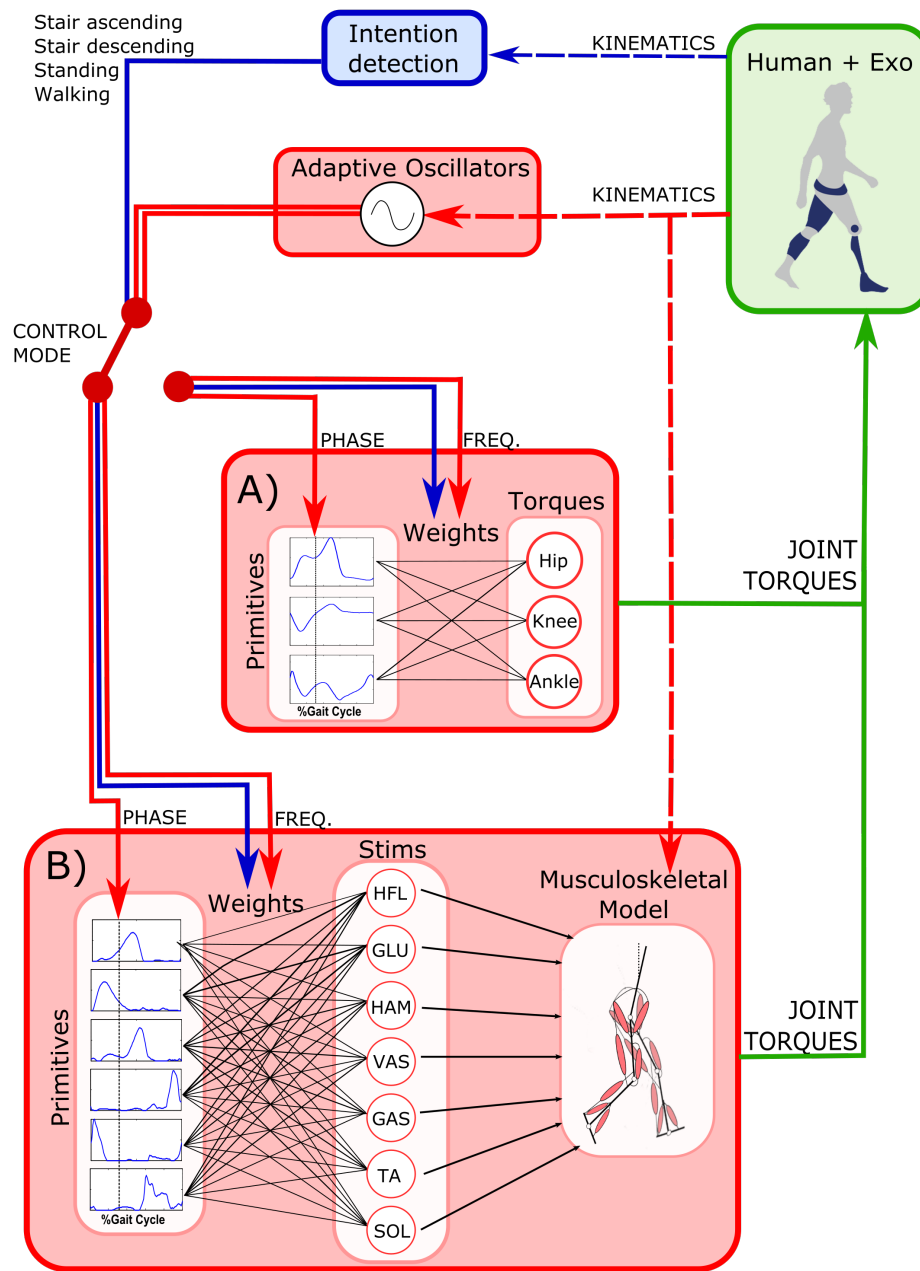


Fig. 1. Bio-inspired controller diagram. The components of the developed controllers (adaptive oscillators and primitive-based controllers) are shown in red. The blue box represents the algorithm detecting the motor intention of the user. The green box represents the human-orthosis coupled system. *Stims.* stands for the muscle stimulations, *Freq.* for the gait frequency, and *Exo.* for the exoskeleton. **A)** Controller based on dynamic primitives (*DLMP*). **B)** Controller based on neural primitives (*NLMP*).

where, t denotes the sample times (in our case, normalized from 0 to 100% of the gait cycle), n the number of primitives and e the number of reconstructed signals, depending on the number of gait patterns and cadences to be considered and on the level of organization of the primitives (*DLMP* or *NLMP*).

The next two sub-sections report the algorithms adopted to extract *DLMP* and *NLMP*.

A. Dynamic-level Primitives

In this case, the objective was to find the minimum set of primitives that can directly reconstruct all leg joint torque profiles from the data set (Table I).

Three sagittal joint torques (hip, knee, and ankle) were extracted for 7 different conditions: 5 different walking cadences and ascending and descending stairs. These torques are displayed in Figure 2 upper left panel.

The decomposition process relied on PCA. From its outcome we kept the number of components necessary to account for at least 95% of the variance. We further assessed the performance of the selected primitives by computing the normalized root mean square error and added components until this error became smaller than 4% between the reconstructed and actual signals. Only 3 primitives were necessary to account for approximately 98% of the data set total variance.

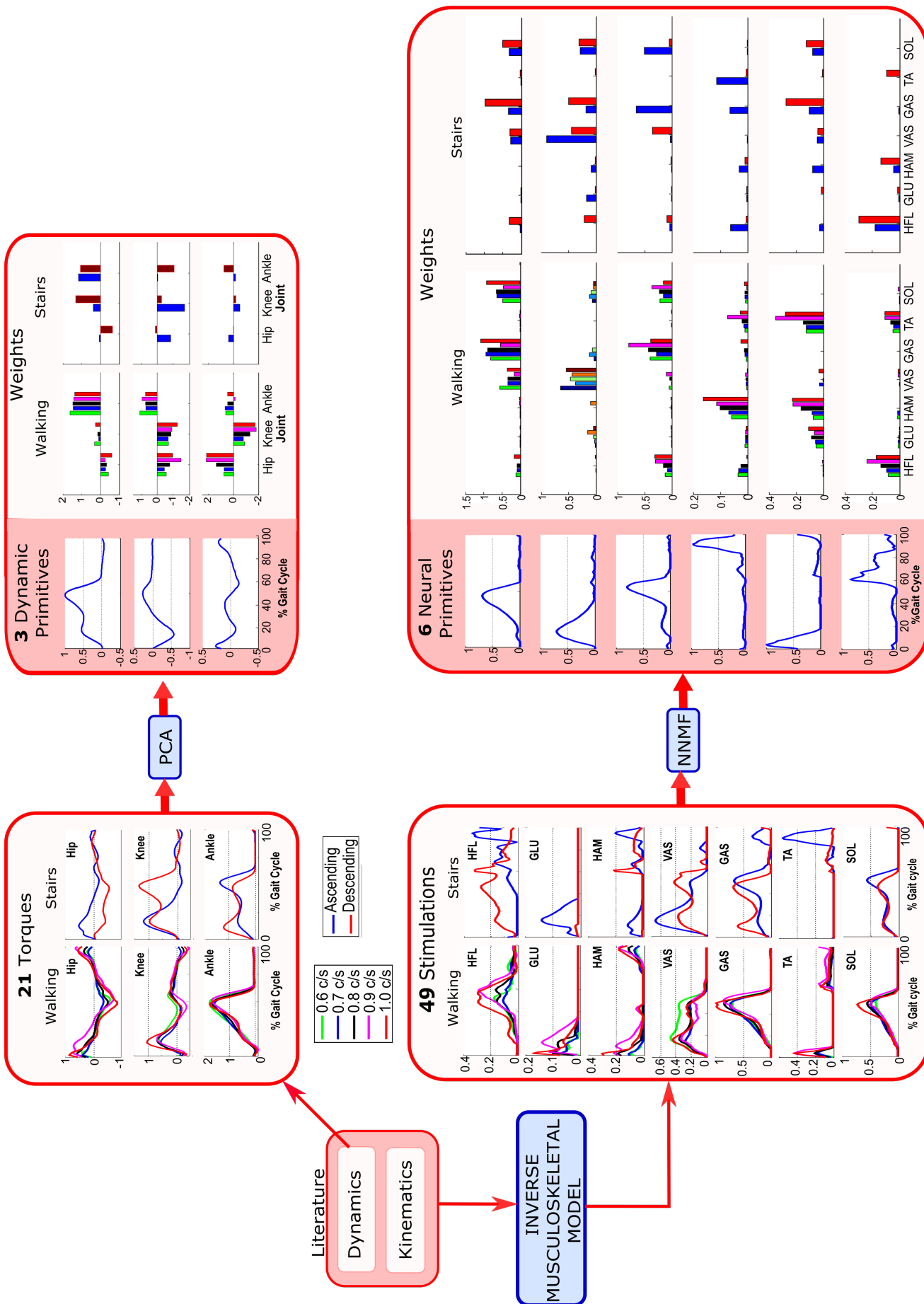


Fig. 2. Primitive extraction process. **Upper diagram:** dynamic primitives *DLMP* extraction from literature torques by means of PCA. **Lower diagram:** Neural primitive *NLMP* extraction. Muscle stimulations are obtained by an inverse musculoskeletal model using kinematic and torque data from the literature. Neural primitives are then obtained from these muscle stimulations by NNMF. In both diagrams, for each component the walking bar graph represents the weight evolution of primitives for the different joint torques (*DLMP*) or muscle stimulations (*NLMP*) as a function of the walking cadence. The bar graph on the right represents the corresponding weights in the case of ascending (blue) and descending (red) stairs.

TABLE I
OVERVIEW OF LITERATURE DATA USED FOR GENERATING THE PRIMITIVES

Reference	Locomotion Task	Cadences (cycles/sec)	Number of subjects
Winter, 1991 [23]	Walking	0.72 c/s	19
		0.88 c/s	19
		1.03 c/s	17
Wang et al., 2012 [24]	Walking	0.82 c/s	5
		0.91 c/s	5
		0.98 c/s	5
		1.04 c/s	5
Koopman et al., 2010 [25]	Walking	0.6 c/s	4
		0.7 c/s	5
		0.8 c/s	8
		0.9 c/s	3
Bradford et al. 1988 [26]	Stairs ascend	X	3
	Stairs descend	X	3
Riener et al. 2002 [27]	Stairs ascend	X	10
	Stairs descend	X	10

These selected primitives are displayed in the upper-right panel of Figure 2 along with the corresponding weights to reconstruct the original data. Finally, the weights for the different walking cadences were simplified by fitting their evolution with second order polynomials.

B. Neural-level Primitives

In this case, the objective was to find the minimum set of components to reconstruct all possible muscle stimulations.

Hereafter, the selected musculoskeletal model is described. Next, we explain how the muscle stimulations used to activate the model were obtained from data in Table I. Finally, the method to identify the target set of artificial motor primitives is presented.

The musculoskeletal model was implemented based on the one developed by [14], comprising seven virtual muscle-tendon units per leg. Each unit captures the following leg muscle groups (Figure 3):

- HFL: Hip flexor muscle. Monoarticular hip flexor.
- GLU: Gluteus muscle. Monoarticular hip extensor.
- HAM: Hamstring muscle. Biarticular knee flexor and hip extensor.
- VAS: Vastus muscle. Monoarticular knee extensor.
- GAS: Gastrocnemius muscle. Biarticular ankle plantar flexor and knee flexor.
- TA: Tibialis anterior muscle. Monoarticular ankle dorsiflexor.
- SOL: Soleus muscle. Monoarticular ankle plantar flexor.

These muscle-tendon units are modelled as Hill-type muscles (Figure 3B): the force F_m being generated by a muscle results from the interaction between a series elastic element (SE), a parallel element (PE), a buffer elasticity (BE) preventing the muscle from collapsing, and the active contractile element (CE) [14]. The force generated by the contractile element depends on l_{CE} and its first derivative v_{CE} , i.e., the muscle length and contraction velocity, respectively, capturing the force-length and force-velocity relationships of a biological muscle.

This model thus introduces a local force feedback in the muscle-tendon unit based on muscle length and velocity. This

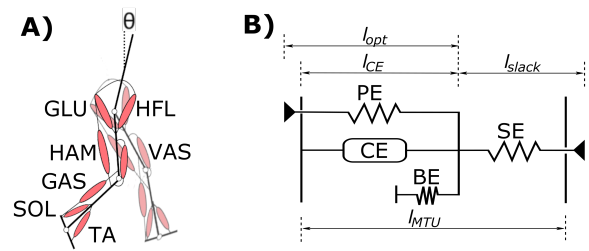


Fig. 3. A) Representation of the 7 main muscle groups actuating one leg. B) Hill-type muscle. Model and figure adapted from [14].

feedback, together with the serial and parallel elasticities, plays a significant role to endow the muscle unit with an intrinsically non-zero impedance and enhance its stability. Afterwards, these muscle forces are converted into muscle torques through geometrical relationships: $\tau_m = r_m \cdot F_m$, where r_m corresponds to the lever arm of the muscle attachment point [14]. Finally, the muscle model computes the joint torques as a function of the torque provided by each muscle:

$$\begin{aligned}
 \tau_{HIP} &= \tau_{HAM} + \tau_{GLU} - \tau_{HFL} + \tau_{IH} \\
 \tau_{KNEE} &= \tau_{VAS} - \tau_{GAS} - \tau_{HAM} + \tau_{LK} \\
 \tau_{ANKLE} &= \tau_{SOL} + \tau_{GAS} - \tau_{TA} + \tau_{LA}
 \end{aligned} \quad (2)$$

where τ_{IH} , τ_{LK} , and τ_{LA} are torques preventing the hip, knee, and ankle from reaching their physical limits [14]. Numerical parameters of the muscle units and of the skeleton geometry were taken from the ones in [14], pending some adaptations to the subjects anthropometry (see Section III).

Neural-primitives reconstruct muscle stimulations. Therefore, these target muscle stimulations have first to be computed from the available kinematic and dynamic data (Table I) before computing the corresponding primitives. For this purpose, an inverse model of the introduced musculoskeletal model was created and scaled depending on the anthropometry reported for each data set. The outcome of this stimulation computation is displayed in the lower left panel of Figure 2.

In order to get a reduced set of primitives that could reconstruct all these muscle stimulations, NNMF was performed. Because NNMF may converge to local minima, the process was repeated 100 times, and the one with the lowest residual error was kept as the solution.

As input to the NNMF process, there were 7 muscle stimulations for 7 different conditions: the 5 different walking cadences and ascending and descending stairs. In coherence with the first decomposition, the first primitives were kept up to accounting for at least 95% of the variance and less than 4% of reconstruction error. This led to 6 components, which also accounted for around 98% of the variance (see Figure 2 lower right panel). Many of the stimulations actually received a negligible contribution for some of the primitives (i.e., several weights were very close to zero). Any coefficients that were at least 10 times smaller than the most influential one were rounded to 0. Also, the weight evolutions across the five walking cadences were interpolated with second order polynomials.

Interestingly, the number of significant primitives found is similar to the literature reports that extracted primitives from

real EMG data [18] [19]. In these former studies, the authors took a larger number of muscles into account. However, they analysed mainly walking and running, while we introduce very different locomotion modes, that is, ascending and descending stairs.

III. EXPERIMENTAL VALIDATION

A preliminary validation experiment of the primitive-based controller was conducted focusing on the walking manoeuvre. In order to deliver the desired assistive torques, the active pelvis orthosis (APO) developed within the CYBERLEGS project was used [28]. This device is an advanced version of a previous laboratory prototype presented in [29]. It has two actuation units that employ a series elastic actuator (SEA) to actively drive the hip flexion/extension movement of each leg¹. Consequently, assistance was provided to both hips for flexion/extension, while the computed assistive torques for the knee and ankle were not delivered to the participants. The APO weighs about 8.5 kg. It was used as a standalone device in this experiment, although it was originally designed to be coupled to a leg exoskeleton and/or a prosthesis which could directly transfer part of its weight to the ground. Consequently, it embeds the electronics and battery for actuating more joints than the hip only, explaining why it is heavier than concurrent solutions.

Tests were conducted with both proposed bio-inspired methods: the *DLMP*-based control with direct torque outputs (Figure 1A); and the *NLMP*-based control, coupled to the musculoskeletal layer (Figure 1B). A fraction of the desired assistive torques generated by either methods was delivered to the joints as a function of the desired level of assistance.

In the case of the *NLMP*, the musculoskeletal model was adapted to each subject. To do so, numerical parameters of the muscle units and of the skeletal model were scaled as a function of the subject's anthropometry. The muscles attachment lever and optimal and slack lengths were modulated proportionally to the subject's height, while the maximal isometric force was modulated proportionally to the square of the height.

Furthermore, in order to assist the participants with the appropriate torque profiles (i.e., the appropriate combination of the primitives and set of weights) it was required to infer their motor intention. This was achieved by using a wearable sensory apparatus (WSA) and the methods reported in [30].

In order to synchronize the control primitives with the actual gait phase of the subject, adaptive oscillators (AOs) were used [22][31]. In this experiment, the hip angles were used as the oscillators inputs, providing the walking frequency (i.e., the gait cadence in cycles/sec) and the instantaneous phase of each leg (see Figure 1). The same primitives were used for both legs, while a separate AO was used for each side. Consequently, the movement phase and frequency were independently detected for each leg and synchronized to the corresponding heel strike instants. This approach allowed the delivery of non-symmetrical torque profiles, since the leg

frequencies were not constrained to be equal, and the heel strike de-phasing was not constrained to be 180 deg.

A. Participants

Nine healthy participants took part in the experiment: two females and seven males. The participants were aged between 22 and 35 years old and weighed between 66 and 85 kg. Participants signed a written consent form before starting the experiments. Two subjects were discarded from the analyses due to problems in oxygen consumption recordings: *S8* because of technical issues, and *S6* because he adopted a highly inconsistent behaviour across the assisted trials. In particular, he increased and decreased his walking speed in some of the assisted trials by 10 to 20%. This led to a high impact on his metabolic consumption, which significantly increased. All the other subjects (including *S8*) walked consistently across trials.

Table II shows the seven remaining participants' features and trials ordering. For the assistive order nomenclature, see Section III-C.

TABLE II
PARTICIPANTS FEATURES AND TRIAL ORDERING. FOR THE ASSISTIVE ORDER NOMENCLATURE, SEE SECTION III-C

Subject	Gender	Age	Weight (Kg)	Order of assistive trials
S1	Male	30	85	TM - LTA - HSA - LSA - HTA - NO
S2	Male	30	76	TM - LSA - LTA - HSA - HTA - NO
S3	Male	27	87	TM - LSA - LTA - HSA - HTA - NO
S4	Female	35	68	TM - LTA - HSA - HTA - LSA - NO
S5*	Female	33	66	NO - LSA - TM - LTA - HSA - NO - HTA
S7	Male	35	82	NO - LTA - HTA - LSA - HSA - TM
S9	Male	22	73	NO - LTA - HTA - TM - LSA - HSA

* For this subject, a technical issue caused the recording to stop before the last trial. An extra session was thus organized, with *HTA* as a unique assisted trial, along with an extra *NO* trial for normalization of oxygen uptake.

B. Experimental set-up

During the experiments, assistance was provided to the hips through the APO device worn by the subjects. One person wearing the full experimental setup is pictured in Figure 4. In the figure, the following elements are visible: APO, WSA, and Oxycon Mobile.

To evaluate the optimal assistance level and the difference between both assistive methods with respect to the transparent mode, the following data were collected during the experiments:

- Position, velocity, and acceleration of the body segments from inertial measurement units (IMUs) of the WSA (Figure 4). IMUs are wireless, battery-powered, and enclosed into small casing appropriate for attachment on body segments. IMUs were placed on both shoes, shanks, and thighs and one was placed on the back.
- Ground reaction forces from sensorized insoles of the WSA (Figure 4).
- Oxygen uptake rate O_2 from a portable Oxycon Mobile (©Carefusion, St.Albans, UK) with a sampling time of 5 sec (Figure 4).

Moreover, the following data were computed in real-time and recorded for off-line analyses: gait phase and cadence of

¹The design of this actuation system is under patent application. "Sistema di Attuazione per Ortesi di Anca"; Italian patent application n. FI/2015/A/000025



Fig. 4. Frontal view of a person wearing the experimental setup. The following components are visible: Oxycon Mobile, APO, the sensory system with inertial measurement units, and the shoes instrumented with custom pressure-sensitive insoles. For more details on the latter two, see [30].

each leg from the oscillators, reference joint torques generated by the controller, and actual hip torque and power provided by the APO.

C. Experimental protocol

Several sub-cases were evaluated depending on the type and level of provided assistance. Assistance was provided with two different methods: through direct torques using *DLMP* or through *NLMP* and the use of the musculoskeletal model.

Before starting the experiment, each subject underwent a phase of familiarization that lasted around 10 minutes. During this phase, the subject walked on a treadmill at a self-selected speed while assistive torques were provided through the pelvis module using both methods. This phase aimed at establishing an estimate of the percentage of assistance to be provided in order to have similar torque magnitudes for both methods and across subjects. In any case, a saturation of 15 N·m was applied for safety reasons.

Afterwards, all subjects underwent a series of 6-minute walking tests (6MWTs) with trials under the following conditions:

- **No APO (NO):** Ground-level walking without wearing the orthosis. It served as a basis for the kinematics and dynamics comparison and to evaluate the natural cadence and oxygen cost during normal walking.
- **APO in transparent mode (TM):** Ground-level walking wearing the APO. The APO was controlled in transparent mode, i.e., rendering zero impedance. This condition served to evaluate the influence of wearing the pelvis module on the natural kinematics, dynamics, cadence, and oxygen cost.

- **Low assistance (LA):** Ground-level walking wearing the APO while providing assistance. This condition was applied twice: a walking trial while providing assistance directly by outputting torques (*LTA*), and a walking trial while providing assistance through the musculoskeletal model (*LSA*). During *LA*, assistive peak torques were in the range between 2 to 4 N·m.
- **High assistance (HA):** Ground-level walking wearing the APO while providing assistance. This condition was applied twice: a walking trial while providing assistance directly by outputting torques (*HTA*), and a walking trial while providing assistance through the musculoskeletal model (*HSA*). During *HA*, assistive torques were in the range between 4 to 6 N·m.

Importantly, subjects performed these trials by walking in a free environment, i.e., not on a treadmill. Specifically, they walked back-and-forth along a corridor of 30 m without stopping at the turns. At the end of each turn, the time was recorded in order to obtain a running-average estimate of the walking speed. In all trials, participants were free to adopt the most comfortable walking speed.

All different trials were randomly applied, except for the *NO* trial. This was due to the fact that placing this trial at the beginning or the end reduced the time needed for conducting the whole experiment and provided an invariant set-up during the rest of the conditions. In order to have some different distribution among subjects, the *NO* trial was placed last for 4 participants and first for the other 3. The exact ordering of the trials for each subject is reported in Table II.

During each trial, the subject followed an established sequence in order to reach steady-state with oxygen consumption: 1 minute sitting on a chair - 1 minute in quiet standing - 6MWT - 1 minute in quiet standing until the VO_2 curve decreases back to steady-state.

D. Data processing

For each subject, the following items were assessed:

- Kinematics during walking, i.e., the hip, knee, and ankle angular position among the different trials (from IMUs).
- Generated total reference torques, i.e., the outputs of the assistive controller.
- Walking speed of the subject.
- Normalized oxygen rate.

During each of the trials, the Oxycon device provided measurements of the oxygen uptake volume VO_2 in ml/min. These were normalized to body weight W in kg and walking speed v in m/min in order to obtain the oxygen cost per meter walked:

$$Cost = \frac{VO_2}{W \cdot v} \left[\frac{ml}{kg \cdot m} \right] \quad (3)$$

An example of the VO_2 recordings normalized to body weight (BW) for a representative subject is reported in Figure 5. When the 6MWT starts, the VO_2 starts increasing consequently. After 2-3 minutes of walking, it stabilizes to a steady-state level.

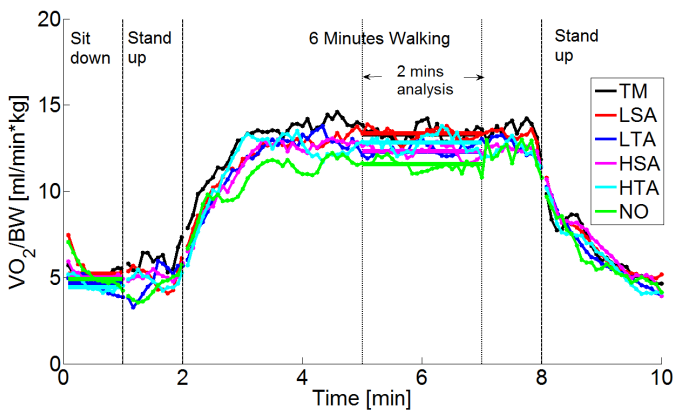


Fig. 5. Smoothed Oxygen uptake volume normalized to body weight for Subject 2 during each of the trials. Vertical lines represent the considered intervals for the data analysis. Horizontal lines represent the median values during the two analysed intervals: sitting down and steady-state walking.

Raw data were filtered with a running average filter over a span of 5 samples. For each of the trials, 2 intermediate minutes of the 6MWT were kept for the analysis. This excluded the first 3 minutes during which oxygen uptake did not reach steady-state yet as well as the last minute, which also showed transients at the end of the trial for some subjects. These last minute transients were probably due to fluctuations in the measurement of the exact duration of the 6MWT as well as the smoothing effect of the data filtering. The median value during the sitting-down phase and this steady-state 2-minute interval were computed for further analyses.

In order to disregard potential fatigue effects over trials and to focus only on the extra oxygen cost required for walking, the VO_2 rates measured during walking were also normalized by subtracting from them the rates measured during the initial sitting-down condition.

Finally, oxygen cost was further normalized to the *TM* trial, which represents 100%, and these results were averaged across all participants for each trial.

In order to assess the impact of the assistive trials in the walking behaviour and the metabolic cost, statistical *t*-tests were performed by individually comparing each of the assistive modes to the *TM* one with $p < 0.05$. These tests were performed to check significant changes in speed, cadence, and normalized oxygen cost.

IV. RESULTS AND DISCUSSION

A. Walking kinematics

Participants walked at their preferred speed and with their preferred pattern during each of the trials. Figure 6 shows the average hip kinematics of all subjects in each of the trials. A reference from the literature is also provided for qualitative comparison [23]. It can be observed that the joint kinematics had very similar profiles across trials and to the one reported in the literature. This shows that, in principle, the assistance does not change the natural locomotion pattern of healthy participants. It also further illustrates the relevance of the computed primitives, since they were extracted from literature data and followed the same kinematics as the participants.

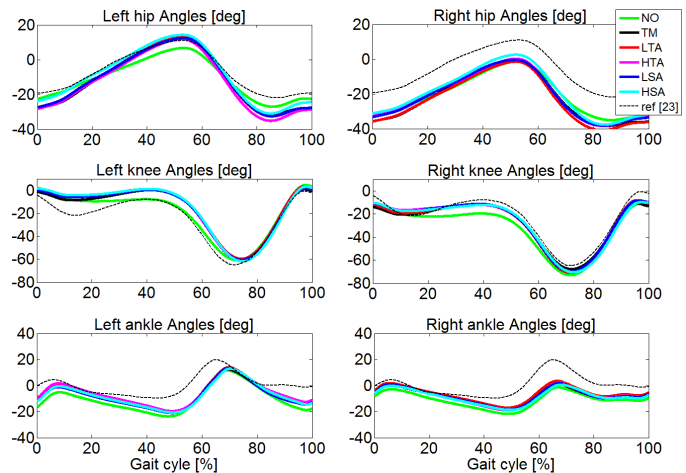


Fig. 6. Kinematics of all joints during the 2 minutes of steady-state walking. The coloured solid lines represent the different trials underwent by the subjects, and the dashed black lines display a reference from the literature for comparison [23]. Positive values represent extension, and negative values represent flexion. This figure shows data averaged across the healthy participants.

In Figure 7, the average speed and cadence during the 2-minute interval of steady-state walking is displayed. These variables are normalized with respect to the *TM* trial for each participant. The walking cadence was estimated from the frequency continuously learned by the adaptive oscillators from the hip angular position. The average subject's cadence during the 2-minute walking interval was thus computed as the median value of the average of the right and left leg's frequency over time.

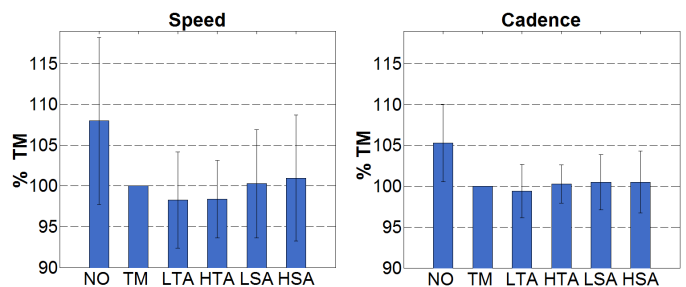


Fig. 7. Walking speed and cadence mean values and standard deviations of the overall group for each of the trials, normalized to the *TM* trial.

We observed that wearing the device (with or without assistance) tended to make the subject walk slower than in the *NO* trial. This was correlated with a similar decrease in walking cadence. In general, the overall walking speed can be decreased (resp. increased) in two concurrent ways: either by decreasing (resp. increasing) the walking frequency, or by decreasing (resp. increasing) the step length. It seems that our participants favoured the former, although no direct measurement of the step length was available. Statistically significant differences for the walking speed with the *NO* trial was reached for the *LTA* and *HTA* trials ($p = 0.0313$ and $p = 0.0137$, respectively). The same trials displayed a significant decrease of the walking cadence ($p = 0.0113$ and $p = 0.0084$, respectively). In sum, there was a significant

reduction of both walking speed and cadence in the *LTA* and *HTA* trials. In the case of *HSA*, there was a significant reduction of the walking cadence with respect to the *NO* trial ($p = 0.0152$); however, the speed reduction did not reach significance ($p = 0.0533$). In the case of *LSA*, there was no significant reduction neither in speed nor in cadence ($p = 0.1823$ and $p = 0.0710$, respectively). In any case, when comparing the *TM* mode with any of the assistive trials, there was no significant difference. In conclusion, wearing the device caused the walking pace to decrease, and no change was observed between the non-assisted and assisted trials.

Interestingly, this connects to a nice model-based prediction: if we assume that the subjects walk at their resonance frequency (i.e., the one that optimizes the exchanges between kinetic and potential energies), increasing their mass when wearing the APO should make this frequency decrease. Indeed, for a mass-spring system (which is often used as a very simplified model of walking [32]), the resonance frequency is proportional to $\sqrt{1/m}$. Therefore, it is logical to observe a decrease in walking cadence when the body mass is augmented, i.e., when the subject wears the device.

B. Walking dynamics

Figure 8 shows the average joint reference torques computed in the different trials. In the case of *NO*, the APO was not worn by the subject, and thus no torque was provided. In the case of *TM*, the torque reference was set to 0, meaning that the powered orthosis was asked to follow the intended movement of the person without hindering it, i.e., with no torque being delivered. In the case of the assistive modes, a fraction of these reference hip joint torques was provided, depending on the desired level of assistance.

In general, all computed torque reference profiles are similar to the ones found in the literature. This was expected since these profiles were precisely generated by primitives constructed from literature data. We can also observe an overall similarity between the torque profiles derived from the *DLMP* and the *NLMP*-based controllers. Again, this was expected since healthy subjects have very similar kinematics to the “ideal” ones that were used to build the primitives. Nevertheless, some differences can be found between both approaches. Focusing on the hip, for example, the *DLMP*-based approach provided larger flexion torque than the *NLMP*-based approach, while the opposite holds for the extension torque. Also, we can observe some divergence in the hip profiles after toe-off (between 65% and 85% of the gait cycle), where the *NLMP*-based control output show a steep decrease in extension followed by a plateau around 0 torque, and the *DLMP*-based control output a smoother transition between flexion and extension torques.

C. Oxygen Cost

From the VO_2 uptake, the normalized oxygen cost of transportation was computed using (3) and the methods reported in Section III-D. A possible fatigue effect within the 6MWT was discarded, because for all considered subjects there was no clear

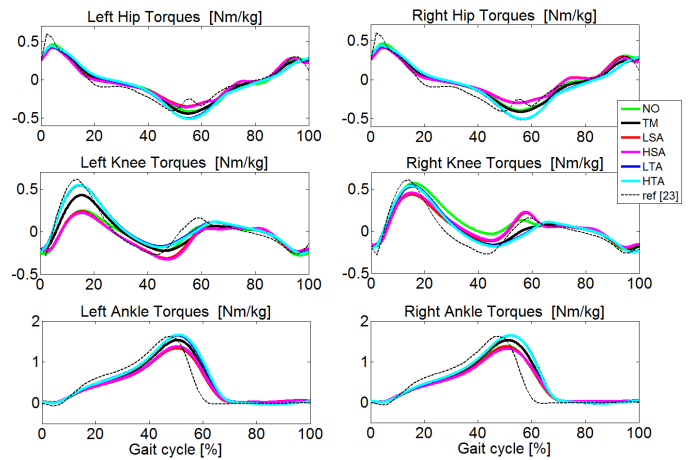


Fig. 8. Reference torques of all joints during the 2 minutes of steady-state walking, normalized to body weight. The coloured solid lines represent the different trials underwent by the subjects, and the dashed black lines display a reference from the literature for comparison [23]. Positive values represent extension, and negative values represent flexion. This figure shows data averaged across healthy participants.

increasing trend of O_2 consumption with time during the trial (see, for example, the records for Subject 2 in Figure 5).

Four of the 7 subjects benefited from all the assistive trials. Two (*S2* and *S9*) benefited for 3 of the 4 trials and displayed a small increment in the last one (less than 10%). Actually, this trial was the last to be tested for each of these 2 subjects, so they could have been impacted by fatigue across trials. One subject (*S7*) did not display a reduction in metabolic cost in any of the assistive conditions. For each subject that benefited from assistance, there was at least one assisted trial with more than 10% improvement with respect to *TM*. *S1*, *S3*, and *S4* even presented trials displaying a decrease in oxygen cost with respect to the *NO* trial. So, in general, the assistive trials managed to bring the subjects’ metabolic rates to a condition in-between *NO* and *TM*, showing a decrease with respect to *TM* but still not enough to compensate for the payload of wearing the device.

Figure 9 shows the average cost data. It displays a general increase of oxygen cost when moving from the *NO* trial to the *TM* trial of about 22%. This increase was mainly due to the burden of wearing the 8.5 kg device, which was originally intended to be coupled to a leg orthosis and/or prosthesis which could transfer part of its weight directly to the ground. Nevertheless, a decrease in cost with respect to *TM* can be observed in any of the assistive modes, although standard deviations reveal large variability in the subjects adaptation during the different trials. *t-tests* of *LTA*, *LSA*, and *HSA* trials with respect to *TM* revealed significant reductions ($p = 0.0146$, $p = 0.0409$, and $p = 0.0322$, respectively). Only *HTA* did not reach significance ($p = 0.2704$). The oxygen cost decrease was the largest for the *LSA* and *HSA* trials, where it reached about 50% of the extra cost caused by wearing the device.

V. CONCLUSION AND PERSPECTIVES

In this work, a novel bio-inspired controller based on motor primitives for locomotion assistance was developed.

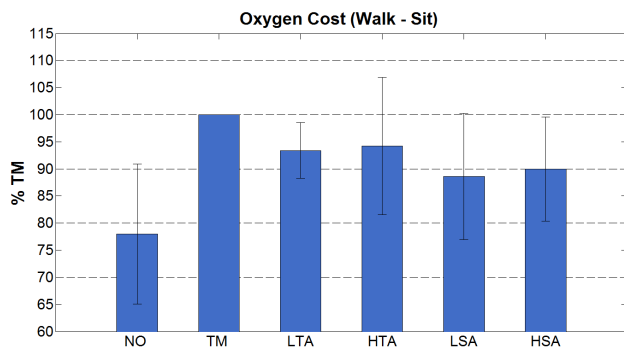


Fig. 9. Oxygen rate mean values and standard deviations of the overall group for each of the trials, normalized to the *TM*.

Based on literature data, a basic set of primitives were extracted that could reconstruct joint torques (by 3 *DLMP*) or muscle stimulations (by 6 *NLMP*) for walking cadences between 0.6 and 1 cycle/sec and for ascending and descending stairs. The controller used this reduced set of primitive signals together with information from a wearable sensory apparatus, i.e., the kinematics (joint angles), and ground reaction forces (swing/stance) to generate reference joint torques. This reduced set of sensors were directly attached to the user and therefore independent of the robot being used. This, together with the direct torque control output, makes the proposed control approach easily transferable to any torque-controlled assistive robot. This is especially true if we consider the *NLMP*-based control, which implement a virtual-musculoskeletal model. Indeed, this controller naturally induces some adaptation to the subject's particular kinematics through artificial muscles but avoids the complex sensor deployment and signal processing required by EMG.

In order to assess the assistive capability of both control approaches, several experiments were conducted. This included two analyses: first, the capability itself of the assistance to decrease the oxygen cost; and second, the difference between using *DLMP* directly outputting torques or using *NLMP* and a musculoskeletal model.

Results on healthy walkers displayed between a 20 and 30% increase of metabolic cost when switching from the *NO* trial to *TM*, namely, when the wearer is able to walk without encountering resistive actions from the orthosis. This reveals that the device weight had a significant negative impact on the subject cost of transport, despite all the efforts made to maximize its transparency. Nonetheless, the tested assistive methods indeed proved to assist the subjects by reducing the oxygen cost with respect to *TM* up to reaching a significant level for three of the four assistive trials. Therefore, it may be forecast that using a lighter exoskeleton would bring this reduction down to lower values than *NO*.

Our method combined different mechanisms to continuously adapt the delivered torques to the subject's actual kinematics. First, *DLMP* were time-scaled as a function of the gait phase and frequency, being continuously and independently monitored for each leg by adaptive oscillators. This opens the possibility to deliver non-symmetrical patterns, a desirable feature for patients with hemi-deficits. Then, the primitives

were multiplied by frequency-dependent weights, guaranteeing the adaptation of the torque profile to the current walking cadence. On top of that, *NLMP* generated stimulations that entered into a musculoskeletal model. This model captured a bio-inspired muscle impedance, so that torques were generated not only as a function of the gait phase and walking frequency but also of the particular subject's kinematics. In brief, the generated torque adapts to the natural walking pattern of each different subject. Therefore, the *NLMP* approach should be more convenient for patients with pathologies causing the natural way of walking to differ from the "ideal" one of healthy subjects. Last but not least, this approach is more prone to integrate other bio-inspired stimulations, such as reflexes or postural control [14].

Future work will focus on similar experiments with patients displaying a pathological gait in order to better assess the relevance of the *NLMP*-based method to adapt to each particular gait.

Finally, the system can easily be adjusted to convey the assistive strategy of a full orthosis or an active prosthesis. This can be done by following the same principles as the APO assistive strategy and adapting the outputs to the necessary control inputs of the device, if not directly torque-driven.

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REFERENCES

- [1] Economic, U. N. D. of. (2013). "World Population Ageing, 2013".
- [2] J. Verghese, A. LeValley, C. B. Hall, M. J. Katz, A. F. Ambrose, R. B. Lipton. "Epidemiology of gait disorders in community-residing older adults". *Journal of the American Geriatrics Society*, 54(2), 255-61, 2006.
- [3] T. Lenzi, M.C. Carrozza, S.K. Agrawal. "Powered hip exoskeletons can reduce the users hip and ankle muscle activation during walking". *IEEE Trans Neural Syst Rehabil Eng.*, 21(6):938-48, 2013.
- [4] M.R. Tucker, J. Olivier, A. Pagel, H. Bleuler, M. Bouri, O. Lamberg, J.R. Millan, R. Riener, H. Vallery, R. Gassert. "Control Strategies for Active Lower Extremity Prosthetics and Orthotics: A Review". *Journal of NeuroEngineering and Rehabilitation*, 12:1, 2015.
- [5] I. Díaz, J.J. Gil, E. Sanchez. "Lower-limb robotic rehabilitation: Literature review and challenges". *Journal of Robotics*, 759764:1-11, 2011.
- [6] T. Yan, M. Cempini, C.M. Oddo, N. Vitiello, "Review of Assistive Strategies in Powered Lower-Limb Orthoses and Exoskeletons", *Robotics and Autonomous Systems*, vol. 64:120-136, 2015
- [7] W. Hassani, S. Mohammed, Y. Amirat. "Real-Time EMG driven Lower Limb Actuated Orthosis for Assistance As Needed Movement Strategy". *Proc. Of the 2013 Robotics: Science and Systems Conference (RSS 2013)*, 2013.
- [8] K.S. Türker. "Electromyography: some methodological problems and issues". *Physical Therapy October*, vol. 73 no. 10 698-710, 1993.
- [9] H. Kazerooni, J.-L. Racine, L. Huang, R. Steger. "On the control of the Berkeley lower extremity exoskeleton (BLEEX)". *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, pp. 4353-4360, 2005.
- [10] A.J. Ijspeert. "Central pattern generators for locomotion control in animals and robots: a review". *Neural Networks*, 21, 642-653, 2008.
- [11] S. Degallier, A. Ijspeert. "Modeling discrete and rhythmic movements through motor primitives: a review". *Biol Cybern*, 103:319-338, 2010.
- [12] X. Zhang, M. Hashimoto. "Synchronization-based trajectory generation method for a robotic suit using neural oscillators for hip joint support in walking". *Mechatronics*, vol 22 (1): 3344, 2012.

- [13] R. Ronsse, T. Lenzi, N. Vitiello, B. Koopman, E. van Asseldonk, S.M.M. de Rossi, J. van den Kieboom, H. van der Kooij, M.C. Carrozza, A.J. Ijspeert. "Oscillator-based assistance of cyclical movement: model-based and model-free approaches". *Med Biol Engineering and Computing*, 49(10):1173-85, 2011.
- [14] H. Geyer, H. Herr. "A Muscle-Reflex Model That Encodes Principles of Legged Mechanics Produces Human Walking Dynamics and Muscle Activities". *IEEE Trans Neural Syst Rehabil Eng*, vol. 18, no. 3, pp. 263-273, 2010.
- [15] J. C. Selinger, S. M. O'Connor, J. D. Wong, J. M. Donelan. "Humans Can Continuously Optimize Energetic Cost during Walking". *Current Biology*, 25(18):p2452-2456, 2015.
- [16] E. Bizzi, V.C.K. Cheung, A. d'Avella, P. Saltiel, M. Tresch. "Combining modules for movement". *Brain Research Reviews*, 57(1):125a-133, 2008
- [17] S.F. Giszter. "Motor primitives—new data and future questions". *Current opinion in neurobiology*, 33:156-65, 2015.
- [18] Y.P. Ivanenko, R.E. Poppele, F. Lacquaniti. "Five basic muscle activation patterns account for muscle activity during human locomotion". *J Physiol*, 556:267-282, 2004.
- [19] G. Capellini, Y.P. Ivanenko, R.E. Poppele, F. Lacquaniti. "Motor patterns in human walking and running". *J Neurophysiol*, 95:3426-3437, 2006.
- [20] T. Flash, B. Hochner. "Motor primitives in vertebrates and invertebrates". *Curr Opin Neurobiol*, 15(6):660-6, 2005.
- [21] S. Degallier, L. Righetti, S. Gay, A. Ijspeert. "Toward simple control for complex, autonomous robotic applications: combining discrete and rhythmic motor primitives". *Auton Robot*, 31:155-181, 2011.
- [22] R. Ronsse, S.M.M. de Rossi, N. Vitiello, T. Lenzi, M.C. Carrozza, A.J. Ijspeert. "Real-Time Estimate of Velocity and Acceleration of Quasi-Periodic Signals Using Adaptive Oscillators". *IEEE Transactions on Robotics*, vol. 29(3): 783-791, 2013.
- [23] D.A. Winter. "The biomechanics and motor control of human gait: normal, elderly and pathological". *Waterloo Biomechanics Press*, 1991.
- [24] J.M. Wang, S.R. Hamner, S.L. Delp, V. Koltun. "Optimizing Locomotion controllers using biologically-based actuators and objectives". *ACM Transactions on Graphics*, 31(4), 2012.
- [25] B. Koopman and W. van Dijk. "Basic gait kinematics: reference data of normal subjects", *University of Twente*, Experimental data, 2010.
- [26] J.M. Bradford, D.A. Winter. "An integrated biomechanical analysis of normal stair ascent and descent". *J. Biomechanics*, vol. 21, No 9, pp 733-744, 1988.
- [27] R. Riener, M. Rabuffetti, C. Frigo. "Stair ascent and descent at different inclinations". *Gait & Posture*, 15(1):32-44, 2002.
- [28] CYBERLEGS [Online]. <http://www.cyberlegs.eu/> [Accessed: 28 Mars 2015].
- [29] F. Giovacchini, F. Vannetti, M. Fantozzi, M. Cempini, M. Cortese, A. Parri, T. Yan, D. Lefeber, and N. Vitiello, "A light-weight active orthosis for hip movement assistance", *Rob. Auton. Syst.*, 2014.
- [30] L. Ambrozic, M. Gorsic, J. Geeroms, L. Flynn, R. Molino Lova, R. Kamnik, M. Munih, N. Vitiello. "CYBERLEGS - A User-Oriented Robotic Transfemoral Prosthesis with Whole Body Awareness Control". *IEEE Robotics & Automation Magazine*, 21(4): 82 - 93, 2014.
- [31] L. Righetti, J. Buchli, A.J. Ijspeert. "Dynamic Hebbian learning in adaptive frequency oscillators". *Physica D*, vol. 216:269-281, 2006.
- [32] H. Geyer, A. Seyfarth, R. Blickhan. "Compliant leg behaviour explains basic dynamics of walking and running". *Proc Biol Sci*, 273, 2861-2867, 2006

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