Motor primitive-based control for lower-limb exoskeletons

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***Abstract*— Assistive technology forecasts better autonomy for people with lifelong disabilities and for the elderly facing motor decline. As the population of developed countries is becoming greyer, there is thus a high probability of observing a significant increase in the demand for assistive locomotion devices. Designing the controller for such devices is not trivial, and requires both to set up a compliant framework and to manage the cross adaptation between the device and its user (the so-called interface). Taking inspiration from neuromechanical principles governing human locomotion is an approach which is currently investigated by several groups to address these challenges.**

In this contribution, we develop a bio-inspired controller based on motor primitives for lower-limb assistance. Motor primitives are combined in order to generate muscle stimulations that serve as neural inputs to a virtual musculoskeletal model, which in turn produces reference sagittal joint torques. This controller is also adaptable to different configurations of lower-limb exoskeletons and sensory inputs.

This paper further reports the validation of the controller through two different experiments. Results showed the capability of the controller to provide coherent joint torque profiles for different configurations and locomotion tasks. These profiles could be used as assistive torques by scaling them as a function of the level of support being required, and transmitting them through an assistive device like an exoskeleton.

I. INTRODUCTION

Design and control of active exoskeletons is a growing field of research nowadays. On one hand, ageing of population is a major issue in most developed countries [1]. Elderly people are more prone to gait disturbances that may derive either from a natural decline of capacities, from peripheral vascular disease, or from accidents like stroke [2][3]. Therefore, new technologies overcoming these disturbances are urgently needed to support a sustainable ageing society.

On the other hand, there is also an incentive to develop such technologies for younger patients with lifelong disabilities. For example, exoskeletons are being developed to assist walking for spinal cord injured patients [4][5]. These robots provide a fantastic hope for paralysed patients not only for retrieving autonomous walking, but also to stand up next to their relatives, and to progress in environments being challenging for a wheelchair, like staircases, etc.

In order to control such devices, several authors explored the use of EMG signals to generate assistive torques [6][7]. However, these face the problem of the complexity of the sensor deployment and the need of heavy signal processing. Others used dynamic models of the exoskeleton or the exoskeleton-human complex [8]. Still, this approach mostly suffers from the lack of accuracy of the model and the need to identify as many different dynamic models as potential users.

A promising approach gets inspiration from the so-called central pattern generators (CPGs) [9][10]. 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. In some cases, AOs were used to adapt pre-recorded profiles to the user gait pattern, which implies adding more profiles every time a new manoeuvre is programmed [11]. 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 [12]. Such approaches are prone to find difficulties while transitioning from one locomotion task to another, e.g., changing from walking to ascending stairs.

In this contribution, we develop a bio-inspired framework that further exploits the concept of CPGs by combining AOs with artificial motor primitives. In particular, we target for the development of a control strategy to assist locomotion. Motor primitives can be defined as forming a basis set of signals governing learned motor behaviours [13]. In other words, they are a set of basic signals that - through proper recombination - are able to generate the large set of muscle stimulations needed for different locomotion tasks. Motor primitives have been widely studied and supported by contributions like [14][15]. For instance, [14] reviewed the experiments showing that 5 time-varying signals could explain the EMG recordings of 13 leg muscles in 3 intact frogs during swimming, jumping, and walking. Similarly, [16][17] extracted 5 to 6 basic components that could explain the measured EMG signals from several human locomotion tasks, such as walking and running at different speeds.

The proposed primitive-based controller is developed to adapt to each subject natural gait pattern. Furthermore, it is designed to be transferable between different devices, possibly using different sensory modalities.

In the following sections, first the general controller is outlined. Then, its application to two different scenarios using

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different sensory inputs, locomotion tasks, and combined assistive devices is described. Afterwards, results are displayed to check the suitability of the generated torque profiles as assistive patterns. Finally, these results are discussed and some conclusions are drawn. The results related to the first experiment being reported were already published in [18].

II. MOTOR PRIMITIVE-BASED CONTROLLER

The motor primitive-based controller emulates the biological process in which a set of high-level commands activate the CPGs located in the spinal cord. These CPGs generate a combination of low-dimensional set of signals outputting a higher-dimensional set of stimulations. These stimulations activate the body muscles giving rise to the desired body movement.

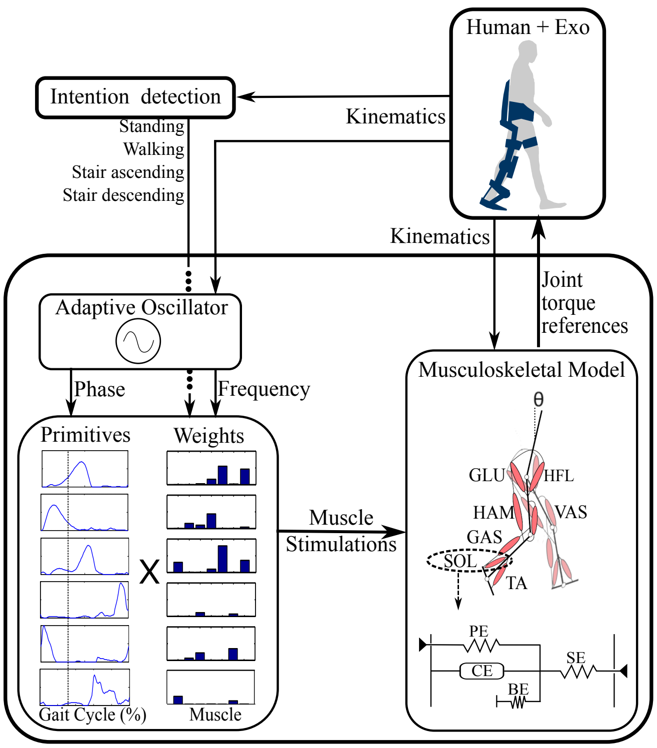


Fig. 1. General control diagram. See the text for a detailed description.

A general diagram of this biologically-inspired framework is depicted in Fig. 1. In such controller, the high-level commands are represented by the intention detection block. In this case, the human intention is classified between standing, walking, ascending, or descending stairs. Note that this could be extended later as a function of the available sensors and the amount of tasks to be detected. Based on the decoded intention, a set low-dimensional primitives are combined generating a high-dimensional set of muscle stimulations. The process to obtain these primitives and to combine them is described in the following sections. In order to select the appropriate primitives and to combine them in a coordinated timing, the gait phase and frequency have to be decoded. This is achieved by using adaptive oscillators (AOs) [20][21].

Next, the generated stimulations activate a musculoskeletal model comprising 7 muscle-tendon units (MTUs), which in turn produces the necessary reference sagittal joint torques. These activations correspond to the biological EMGs. Finally, the human-exoskeleton block captures the dynamical interactions between the user and the exoskeleton.

A. Musculoskeletal model

The musculoskeletal model was implemented based on the one developed by [19] in which each leg is driven by seven virtual MTUs. Each MTU captures the following leg muscle groups: hip flexor muscles (HFL), gluteus (GLU), hamstring (HAM), vastus (VAS), gastrocnemius (GAS), tibialis anterior (TA), and soleus (SOL) (Fig. 1). These MTUs were modelled as Hill-type muscles (Fig. 1, bottom right). The force developed by each muscle F_m comes from the interaction between a series elastic element (SE), a parallel elastic element (PE), a buffer elasticity (BE) preventing the muscle from collapsing, and the active contractile element (CE) [19]. From F_m, muscle torques were obtained through geometrical relationships: $\tau_m = r_m \cdot F_m$, where r_m corresponds to the lever arm of the muscle attachment point [19]. Each of these muscle torques contribute to generate reference torques of the sagittal leg joints (hip, knee, and ankle):

$$\begin{aligned} \tau_{HIP} &= \tau_{HAM_{hip}} + \tau_{GLU} - \tau_{HFL} + \tau_{lH} \\ \tau_{KNEE} &= \tau_{VAS} - \tau_{GAS_{knee}} - \tau_{HAM_{knee}} + \tau_{lK} \\ \tau_{ANKLE} &= \tau_{SOL} + \tau_{GAS_{ankle}} - \tau_{TA} + \tau_{lA} \end{aligned} \tag{1}$$

where τ_{lH}, τ_{lK}, and τ_{lA} captured torques preventing the hip, knee, and ankle to reach their mechanical limits [19]. Note that these relationships clearly captured the bi-articular nature of GAS and HAM, since they produce torques across two joints. Numerical parameters of the MTUs and of the skeleton geometry were taken from the ones in [19], and adapted depending on the subjects anthropometry.

B. Primitives

In order to activate the musculoskeletal model, the high-dimensional set of stimulations were generated by the use of a lower-dimensional set of primitives. To find these primitives, a database of stimulations was created to which non-negative matrix factorization (NNMF) was applied. Such technique extracts a linear combination of primitives and the corresponding weights in order to minimize the difference between the original signals and the reconstructed ones.

This stimulation database was derived from kinematic and dynamic data collected from the literature (see Table I). In order to get the muscle stimulations from these kinematic and dynamic data, an inverse model of the musculoskeletal model was created and scaled depending on the anthropometry reported for each data set.

The obtained stimulations were normalized with respect to time as the percentage of gait cycle (0-100% with 0% being coincident with the corresponding leg foot strike). Furthermore, in order to simplify the primitive extraction process, stair stimulations were averaged together and walking ones were grouped and averaged in five bins of walking cadences,

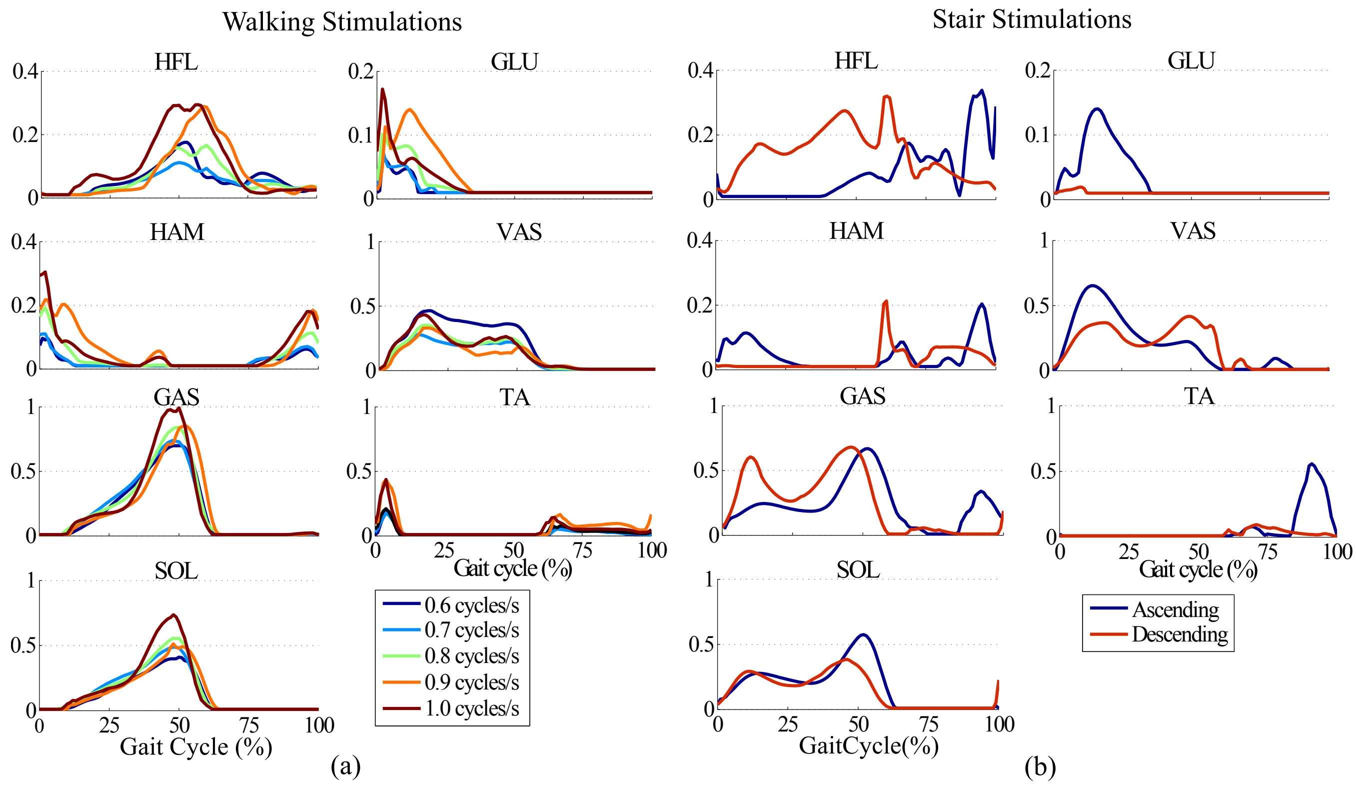


Fig. 2. Muscle stimulations for the 7 MTUs during (a) walking at 5 different cadences and (b) ascending/descending stairs

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. The outcome of this stimulation computation is displayed in Fig. 2. More details are available in [18].

TABLE I
OVERVIEW OF LITERATURE DATA USED

Reference	**Locomotion Task**	**Cadences** (cycles/sec)	**Number of subjects**
Winter, 1991 [22]	Walking	0.72 0.88 1.03	19 19 17
Wang et al., 2012 [23]	Walking	0.82 0.91 0.98 1.04	5 5 5 5
Koopman et al., 2010 [24]	Walking	0.6 0.7 0.8 0.9	4 5 8 3
Bradford et al., 1988 [25]	Stairs ascend Stairs descend	X X	3 3
Riener et al., 2002 [26]	Stairs ascend Stairs descend	X X	10 10

To finally get a reduced set of primitives, NNMF was applied. Because NNMF may converge to a local minima, the process was repeated 100 times, and the one with the lowest residual error was kept as final solution. As input to the NNMF process, there were thus 7 muscle stimulations for 7 different conditions: 5 different walking cadences and ascending and descending stairs. Primitives were kept up to accounting for at least 95% of the variance and less than 4% of the reconstruction error. This lead to 6 components, which accounted for around 98% of the variance. Next, the weight evolutions across the five walking cadences were interpolated with second order polynomials. The result of this primitive and weight extraction process is depicted in Fig. 3.

Interestingly, the number of significant primitives to be kept was similar than in the literature reports that extracted primitives from real EMG data [16][17]. In these former studies, the authors took a larger number of muscles into account. However, they analysed mainly walking and running, while we introduced very different locomotion tasks, that is, ascending and descending stairs.

In order to properly combine the primitives as a function of the gait parameters, AOs were used (see [20] for details). The signals serving as input for the AOs were the hip angles, due to their stable periodic features during different locomotion modes. Furthermore, they were available with the diverse sensory apparatus being used. From this input, AOs provided a real-time estimate of the gait phase and frequency [20]. Moreover, a correlation factor could be adjusted between 0 and 1 to set up the smoothness of the phase reset at the foot strike instant [21]. Dedicated tuning of these parameters was done for each experimental scenario.

III. CONTROLLER VALIDATION

In order to validate the correct real-time functioning of the above presented controller, its versatility, and the suitability of the generated assistive torque profiles, two

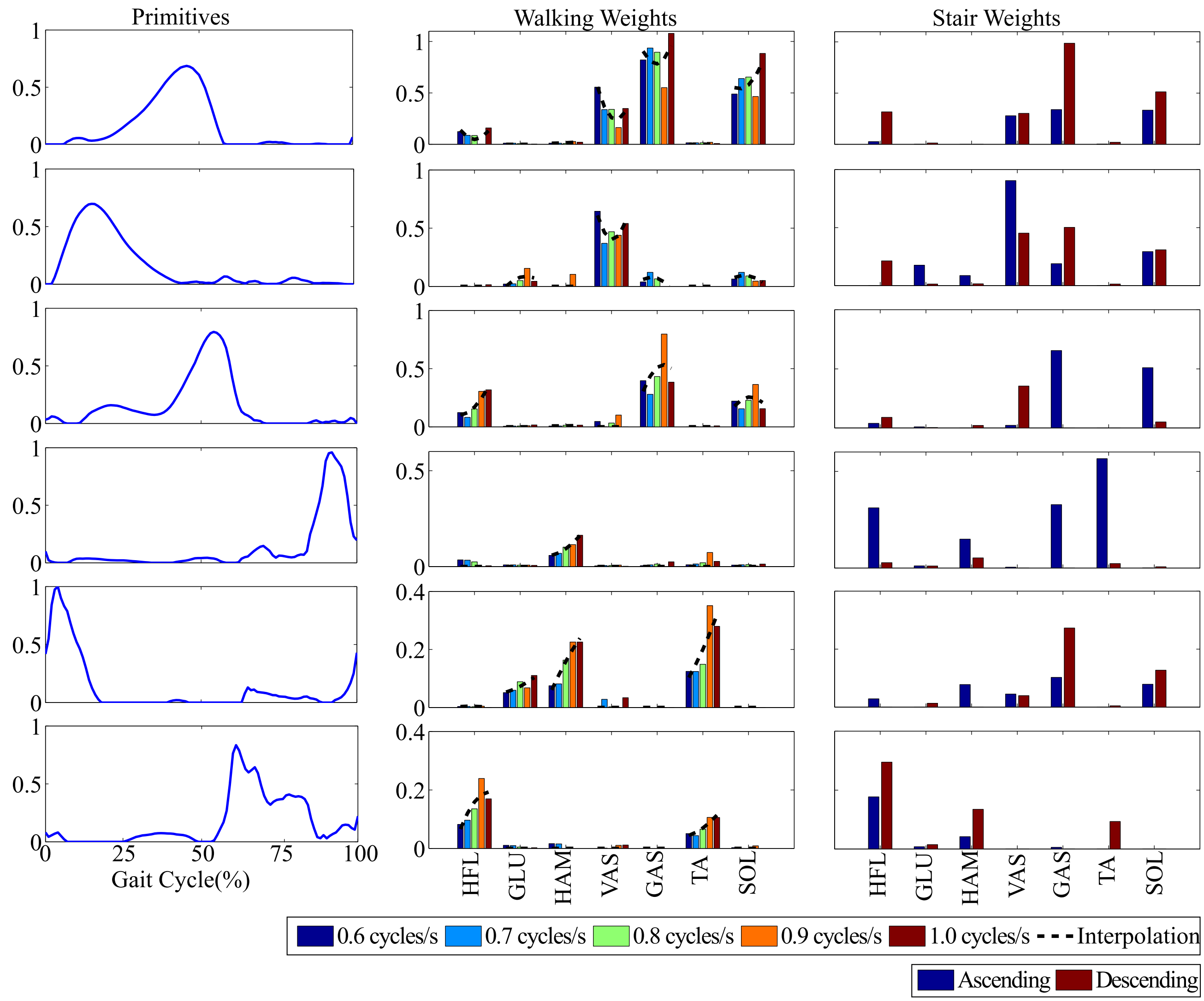


Fig. 3. The six selected primitives and their corresponding weights for the different walking cadences and for ascending/descending stairs. Primitive weights across the different walking cadences were further interpolated by second order polynomials (dotted black lines).

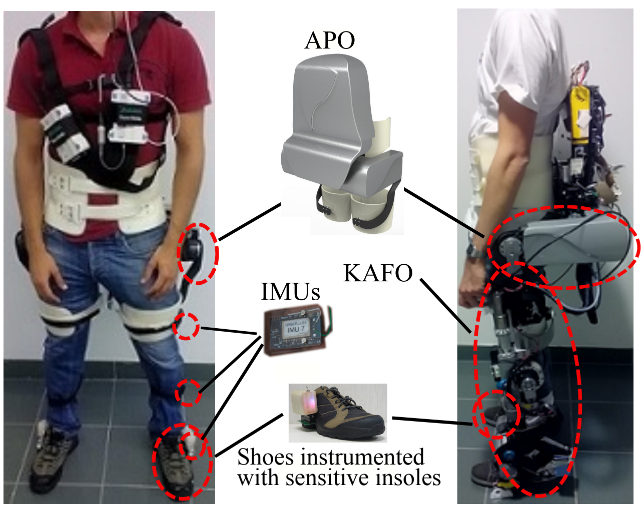
different scenarios were evaluated. In both cases healthy subjects wore set-ups embedding different sensory apparatus and exoskeletons. The subjects walked in transparent mode, i.e. the exoskeleton followed the intended movement of the person without hindering it. Said differently, the reference torques being computed by the controller were not delivered through the exoskeleton.

During the first experiment, 7 subjects were evaluated while walking back-and-forth along a corridor of 30 m during 6 mins. Subjects wore an active pelvis orthosis (APO) developed within the CYBERLEGs project[1]. This device is an advanced version of a previous laboratory prototype described in [27]. As sensory input, position, velocity, and acceleration of the body segments were extracted from inertial measurement units (IMUs) of a wearable sensory apparatus. This further included sensorized insoles to measure the ground reaction forces (GRF) and center of pressure (CoP) of each foot. Finally, to infer the motor intention of the user, the methods reported in [28] were used. In this case, one adaptive oscillator was used for each leg taking as input the corresponding hip angle, so that independent gait parameters were obtained for each leg. The parametrization values for the oscillators were chosen following the guidelines described in [20][21]. The correlation factor in this case was set to 0.5, so that half of the phase error at foot strike was corrected every cycle. This was found as an optimum between phase error correction and smooth changes of cadence. Further details about this experiment are reported in [18]. One subject wearing the full experimental set-up is pictured in Fig. 4a.

In the second experiment, 7 subjects were evaluated while performing a track including ground level walking, ascending, descending stairs, and U-turns. Subjects wore the same

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

APO as in the first experiment, augmented with a knee-ankle-foot orthosis (KAFO) on the left leg [29]. The full coupled exoskeleton was again set to be transparent for the user. As sensory input, angles of the left hip, knee and ankle were taken from the joint encoders of the exoskeleton. Again, a sensorized insole was placed under the right foot in order to discriminate between the stance/swing phases and to reset the phase of the adaptive oscillator at foot strike. Because transitions between very different locomotion tasks were envisioned, the correlation factor in this case was set to 1, so that the phase error at foot strike was entirely corrected within one cycle. Finally, intention detection was based on a real-time locomotion mode recognition presented in [30]. This method is based on a fuzzy-logic classifier using the hip joint angle and foot center of pressure as inputs. One subject wearing the set-up for this experiment is depicted in Fig. 4b.



(a) (b)

Fig. 4. (a) Picture of one subject wearing the first experimental set-up. The following components are visible: APO, the sensory system with inertial measurement units (IMUs), and the shoes instrumented with custom pressure-sensitive insoles. For more details on the latter two, see [28]. (b) Picture of one subject wearing the second experimental set-up. The following components are visible: APO, KAFO, and the shoes instrumented with custom pressure-sensitive insoles.

An overview of the characteristics of both experiments is provided in Table II.

TABLE II

OVERVIEW OF EXPERIMENTAL PARAMETERS

	Experiment 1	Experiment 2
Tasks	Ground level walking	Ground level walking Ascend/descend stairs
Exoskeleton	APO	APO + KAFO
Correlation factor	0.5	1
Sensory input	IMUs 2 insoles	Encoders 1 insole
Intention detection	IMUs GRF, CoP [28]	Hip Encoder CoP [30]

During both experiments, kinematics reading from the corresponding sensory apparatus together with the generated reference torque profiles were recorded. In the case of the first experiment, the average value during 2 mins of steady state walking (minutes 4 and 5) was kept for the analyses. For the second experiment, steady state was considered to be reached when the movement was synchronized with the adaptive oscillator (phase error at foot strike smaller than 0.63 rad, that is, 10% of the gait cycle).

IV. RESULTS

In this section, recorded results from both experiments are reported. These include the recorded kinematics from the respective sensory apparatus and the corresponding generated reference torque profiles. Such profiles are normalized with respect to the body weight of each subject and compared to references from the literature [22][25][26]. The profiles are further normalized in time with respect to the gait cycle duration, since the subjects walked at their preferred speed and cadence during both experiments.

Fig. 5 displays the joint kinematics and generated assistive torques for the first experiment. Although only a hip exoskeleton was worn by the subjects, torque references for all joints were obtained via the proposed primitive-based method.

Fig. 6 displays similar results for the second experiment. The figure reports the kinematics and generated assistive torques for 3 different locomotion tasks: ground level walking, ascending stairs, and descending stairs. The reference torque profiles were generated for the left leg only, since only this leg was equipped with the full exoskeleton and thus with sensors.

V. DISCUSSION

In this contribution, the ability of a biologically inspired controller based on motor primitives to produce appropriate reference sagittal joint torques was examined. In this controller, motor primitives generated muscle stimulations which activated a virtual musculoskeletal model producing joint torques to be delivered for locomotion assistance. This structure involved several levels of adaptability. First, primitives were combined depending on the motor intention and gait frequency and phase. Therefore, the produced stimulations were adapted as a function of these gait parameters. Afterwards, the musculoskeletal model adjusted the stimulations as a function of the actual locomotion pattern of the subject to provide the corresponding assistive torques. This dependency was implemented through Hill muscle models, capturing the compliance of biological muscles. This means that, for the same locomotion task, phase, and gait cadence, the generated reference torque profiles adapted to different subjects with different gait patterns. Furthermore, the musculoskeletal model depended on the subject anthropometry, so that a taller subject generated larger muscle forces, and thus larger joint torques.

From results of both experiments (Figs. 5 and 6), it can be observed that the produced reference torques were consistent among subjects, and were also similar to those reported in different references from the literature. This reveals that the controller indeed could cope with different configurations and sensory inputs while providing appropriate outputs.

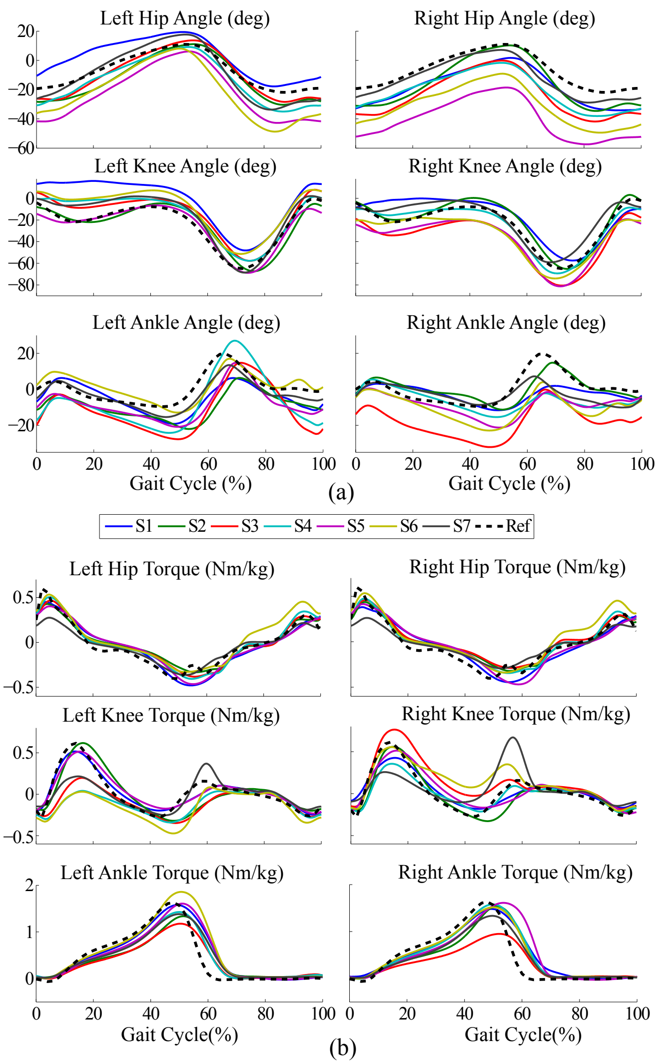


Fig. 5. Results from the first experiment. (a) Recorded kinematics for both legs. (b) Generated reference sagittal torque profiles normalized to body weight. Ref corresponds to [22]. Data were independently averaged for each of the 7 subjects (different colors).

Therefore, it could be envisioned to use a scaled profile of these torques as assistive joint signals, i.e. as torque references for the exoskeleton. Note that results closing this loop between humans and the APO (experiment 1) are reported in [18]. Adaptability can be observed by scrutinising the different generated torque patterns. For example, during the first experiment, subject 3 (S3) showed more knee flexion at the beginning of the gait cycle for the right leg than for the left one (Fig. 5a). This corresponded to a higher knee extension torque, that prevented the knee from collapsing at foot strike (Fig. 5b). On the other hand, changes due to gait parameters and/or anthropometry can be observed in the ankle torques generated during the second experiment, in the stair ascending task (Fig. 6b). Similar ankle kinematics of S2 and S7 gave rise to considerably different peak magnitudes

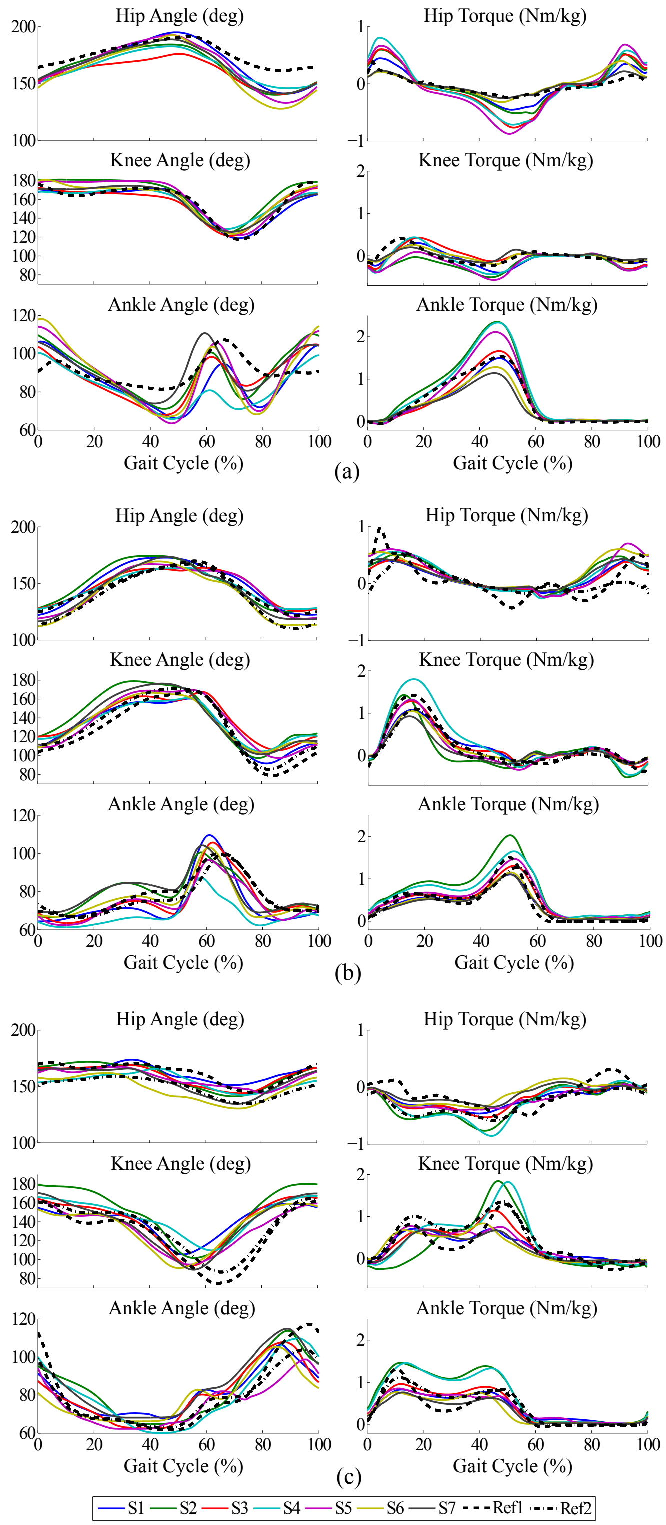


Fig. 6. Results obtained from the second experiment. Kinematics and corresponding reference sagittal torque profiles normalized to body weight of the left leg for (a) ground level walking, (b) ascending stairs, and (c) descending stairs. Ref1 corresponds to [22] for walking and [25] for ascending/descending stairs. Ref2 corresponds to [26]. Data were independently averaged for each of the 7 subjects (different colors).

in the corresponding torque profiles. S2 produced higher torque references, because this subject walked faster that S7 and was taller. Modulations across the different detected locomotion tasks can be directly observed in the different profiles generated during the second experiment (Fig. 6).

Last but not least, the results reveal that special attention must be paid when placing the different sensors and retrieving the kinematic values. Indeed, misalignments between the sensors and the biological limbs or joints could bring variations of the measured kinematics, which would then perturb the desired torque estimation. For example, when comparing the ground level walking task of first and second experiments, it can be observed that the recorded kinematics in the second experiment were more homogeneous across subjects. This was likely due to the fact that kinematics were measured from IMUs in the first case, therefore requiring a thorough calibration procedure, whereas they were measured with absolute encoders in the second case, thus offering a more consistent placement across subjects.

VI. CONCLUSIONS

In this paper, a biologically-inspired controller based on motor primitives for locomotion assistance was presented. The same set of of primitives were used to generate torque references for the hip, knee, and ankle during walking at different cadences, stair ascending, and stair descending. These joint torques could be applied as assistive profiles by scaling them as a function of the level of assistance being required.

Furthermore, this controller has proved to work with different exoskeleton set-ups and diverse sensory devices, showing its adaptability to different platforms.

Future work will focus on testing the presented approach with subjects displaying pathological gaits, in order to assess its actual assistive capability. Also, it is envisioned to increase the literature references in order to enlarge the set of locomotion tasks and cadences.

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