# Oscillator-based Walking Assistance:
# a Model-free Approach

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*Abstract*—In this paper, we extend our recent results of oscillator-based assistance to the case of walking. The adaptive oscillator used in this paper is capable of predicting the angular position of the user's joints in the future, based on the pattern learned during preceding cycles. Assistance is then provided by attracting the joints to this future position using a force field in a compliant lower-limb exoskeleton. To demonstrate the method efficiency, we computed the metabolic energy expended by the participants during a walking task, with and without assistance. Results show a significant decrease of energy expenditure with the assistance switched on, although not to a point to entirely compensate for the burden due to the exoskeleton lack of transparency. The results further show changes in the kinematics: with assistance, the participants walked with a faster cadence and ampler movements. These results tend to prove the relevance of designing assistance protocols based on adaptive oscillators (or primitives in general) and pave the way to the design of new rehabilitation protocols.

## I. Introduction

All robots used for movement assistance or rehabilitation intimately interface with humans, and therefore require to properly address the challenges related to this close interaction [1]. This is particularly the case for lower-limb exoskeletons, their structure being generally parallel to the human leg [2], [3]. Any human movements can be considered as a "perturbation" for the robot controller, which has to decide whether this perturbation has to be rejected, or whether the controller has to be adapted. On the broad spectrum of possible interaction levels, the two extremes are unidirectional: (i) the user is enslaved to the robot; and (ii) the robot is enslaved to the user. The first case is well exemplified by the early versions of lower-limb rehabilitation devices, which forced the user to follow pre-specified trajectories using stiff controllers [4], [5]. This approach however proved to be suboptimal, due to its inherent limitation to promote voluntary movements. As a

consequence, "assist-as-needed" emerged as a new standard [6]–[9]. The other extreme comprises the cases were the robot is used to amplify the torque produced by the human, which can be estimated e.g. by sensing the surface EMGs [10], [11]. This approach has also intrinsic limitations due to the poor accuracy and potential invasiveness (skin irritation, etc) of EMG sensing.

Recently, we proposed a new paradigm for assistive robotics which combines the advantages of both approaches [12], [13]: Providing a trajectory-free movement assistance without requiring complex sensing. The idea behind our approach was to incorporate some a priori knowledge about the movement within the robot controller — as a sort of primitive [14] — and to use the intrinsic adaptivity of this primitive to constantly adapt to the user intention. Concretely, this was achieved by coding our primitive as a system of differential equations with desired dynamical behavior [15]. Our first contributions focused on a proof of concept: a simple sinusoidal movement about the elbow around the vertical position. Therefore, the primitive we used was a single adaptive oscillator capable of learning the movement features (amplitude, frequency, etc) [16], [17]. Using an inverse dynamical model, we were able to estimate the torque applied by the human, and to feedback a fraction of it to provide assistance.

The goal of this paper is to extend this approach to walking, likely the most functional rhythmic activity of daily life. As a consequence, two extra challenges appear with respect to the simple elbow experiment: (i) the joints do not follow sinusoidal patterns, such that their trajectory envelope cannot be assumed to be known a priori; and (ii) deriving an accurate inverse model is much more difficult, mainly because of the discontinuities due to contacts with the ground. To solve the first challenge, we propose a new primitive, which couples the

adaptive oscillator to a non-linear filter, learning the trajectory envelope [18]. To solve the second challenge, we propose a model-free version of our approach, by implementing the assitive torque with an adaptive force field.

We tested our approach using the LOPES, a lightweight lower-limb exoskeleton with compliant actuators [9], [19]–[21]. We monitored the energy expended by human subjects from their oxygen consumption and carbon dioxide expulsion, during walking with and without assistance. The goal of this paper is to establish that our controller helped the users during walking, such that they reduced their level of energy expenditure with respect to the unassisted case. For the sake of simplicity, we assisted only the hips and we report results related to steady-state behavior.

## II. METHODS

### A. Walking assistance using adaptive oscillators

In this section, we will describe the algorithm we used to provide walking assistance. We will explain this algorithm sequentially, starting from an oscillator that is tuned to filter a single DOF movement along a sinusoidal pattern, to end up with an assistance method that is suitable for several joints and the non-sinusoidal profiles encountered in human walking.

*1) Oscillator-based filtering of a sinusoidally moving joint:* The central element of our assistance method is an adaptive oscillator, a tool developed by Righetti et al. [16], [17] and used in many applications [13], [22]. Here, we used a simplified version of the modified Hopf oscillator proposed in [16], by projecting this oscillator into polar coordinates and keeping the phase equation only. We simply obtained an augmented phase oscillator [17]:

$$\dot{\phi}(t) = \omega(t) + \nu F(t) \cos \phi(t), \qquad (1)$$

where, $\phi(t)$ is the oscillator phase, $\omega(t)$ its intrinsic frequency, and $\nu$ the learning parameter determining the speed of phase synchronization to the periodic teaching signal $F(t)$. In order to learn the frequency of the teaching signal $F(t)$, instead of doing mere synchronization only, the oscillator frequency was turned into a new state variable, integrating the phase update:

$$\dot{\omega}(t) = \nu F(t) \cos \phi(t). \qquad (2)$$

From (2), it can be established that the integrator argument sums up to zero over one period (i.e. $\omega$ converges) if the frequency $\omega$ is equal to the frequency of the teaching signal. As such, Righetti et al. developed an *adaptive* oscillator, having the capacity to constantly adapt its intrinsic frequency to the teaching signal frequency, and to keep this input frequency in memory, i.e. in the state variable $\omega(t)$.

Let us now assume (i) that the joint to be assisted follows a sinusoidal pattern, i.e. $\theta(t) = \alpha_{1,in} \sin(\omega_{in} t) + \alpha_{0,in}$, where $\alpha_{1,in}$, $\omega_{in}$, and $\alpha_{0,in}$ are the amplitude, frequency, and offset of this input, respectively; and (ii) that the adaptive oscillator (1), (2) is synchronized with this input. As a consequence, a filtered version of $\theta(t)$ can be obtained by:

$$\hat{\theta}(t) = \alpha_1(t) \sin \phi(t) + \alpha_0(t), \qquad (3)$$

where $\alpha_1(t)$, $\phi(t)$, and $\alpha_0(t)$ are supposed to converge to the corresponding input variables. Righetti et al. [23] showed that this convergence is guaranteed by using the difference between the input $\theta(t)$ and the filtered (or estimated) input $\hat{\theta}(t)$ as teaching signal: $F(t) = \theta(t) - \hat{\theta}(t)$, and by implementing the following integrators for learning the amplitude and offset:

$$\dot{\alpha_0}(t) = \eta F(t), \qquad \dot{\alpha_1}(t) = \eta F(t) \sin \phi(t), \qquad (4)$$

where $\eta$ is the integrator gain. Again, (2) and (4) reach steady-state when $F(t) = 0$, i.e. when $\hat{\theta}(t) = \theta(t)$. If $\theta(t)$ is only quasi-sinusoidal, i.e. if $\alpha_{1,in}$, $\omega_{in}$, and $\alpha_{0,in}$ slowly vary with time, $\hat{\theta}(t)$ will be a low-pass filtered version of $\theta(t)$, but, importantly, both will still be phase-synchronized on average. This is a critical difference between this approach and classical low-pass filtering, which unavoidably introduces delay.

In [12], [13], we used this approach to retrieve not only the filtered position, but also the filtered velocity and acceleration of the elbow during (quasi-)sinusoidal movements, and to assist the movement by using an inverse dynamical model of the elbow+forearm. This approach is however unrealistic in walking assistance, due to the complex dynamics introduced by ground contacts, and the non-sinusoidal profile of the leg joints during walking.

*2) Real-time Fourier decomposition of non-sinusoidal but periodic signals:* If the input signal is periodic but non-sinusoidal, Righetti et al. [23] proposed to extend the method explained above by putting several of these oscillators in parallel (see the upper part of Fig. 1). As such, each of these oscillators should learn one frequency component of the input signal, providing therefore a kind of real-time Fourier decomposition. We slightly adapted the equations of [23] by assuming that the input signal is periodic. Therefore, only the main frequency has to be learned, the others being multiples of it. Concretely, (1), (2), and (4) are changed to:

$$\begin{aligned}
\dot{\phi}_i(t) &= i\omega(t) + \nu F(t) \cos \phi_i(t), \\
\dot{\omega}(t) &= \nu F(t) \cos \phi_1(t), \\
\dot{\alpha}_i(t) &= \eta F(t) \sin \phi_i(t),
\end{aligned} \qquad (5)$$

with $F(t) = \theta(t) - \hat{\theta}(t)$, $\hat{\theta}(t) = \sum_{i=0}^{K} \alpha_i(t) \sin \phi_i(t)$, and $i \in [0, K]$ are the $K$ parallel oscillators. Note that, in (5), the 0th oscillator is still a simple integrator, learning the input offset, with $\phi_0(t) = \phi_0(0) = \pi/2$.

*3) Coupling with a kernel-based non-linear filter:* During pilot tests, a problem appeared when using the pool of adaptive oscillators (5): A large number of oscillators was required to properly learn dwell intervals within the joint signals, like e.g. the plateau in the knee profile during the stance phase of walking (see Fig. 2). For the sake of completeness, we further mention that this method turned out to be non entirely satisfying when we attempted to estimate the joint velocity and acceleration, similarly to [12], [13], although these estimates were not required for the method presented here. Indeed, the successive derivatives amplify the frequency components by a factor $i\omega$, such that truncating the signal to its $K$ first harmonics induced large errors in the derivatives estimates.
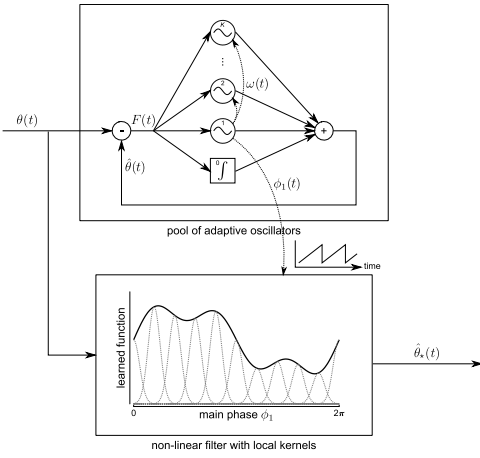
Fig. 1. Online learning of a periodic but non-sinusoidal input signal $\theta(t)$. The upper block is a pool of adaptive oscillators (1), (4), decomposing the input into a real-time Fourier series. The lower block is a kernel-based non-linear filter, mapping the phase of the main harmonic $\phi_1(t)$ to the input envelope. Adapted from [18].
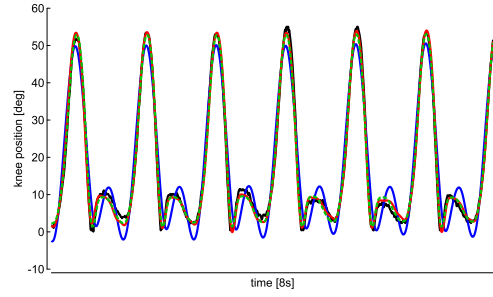


Fig. 2. Different filters applied to the angular displacement of the knee during walking (8 representative seconds are shown): in black: the raw signal; in blue: filtering with a pool of 3 adaptive oscillators; in red: filtering with a pool of 11 adaptive oscillators; and in dashed green: filtering with a pool of 3 adaptive oscillators and a non-linear kernel filter.

To avoid these inherent drawbacks associated with the parallel processing of a limited number of oscillators (5), we coupled the pool of adaptive oscillators to a kernel-based non-linear filter, similarly to [18] (Fig. 1). Note however that we simplified the derivations made in [18] since our application did not target imitation learning, but only filtering.

This is formulated as a supervised learning problem:

$$\hat{\theta}_\star(t) = \frac{\sum \Psi_i(\phi_1(t))w_i}{\sum \Psi_i(\phi_1(t))}, \qquad (6)$$

where $\Psi_i(\phi(t)) = \exp\left(h(\cos(\phi(t) - c_i) - 1)\right)$ is a set of $N$ Gaussian-like kernel functions. The parameter $h$ determines their width, and $c_i$ their center (equally spaced between 0 and $2\pi$ in $N$ steps). This algorithm then constructs a series of local mappings of the input $\theta(t)$ as a function of the phase $\phi_1(t)$, and an estimate of the input $\hat{\theta}_\star(t)$ from a weighted sum of these mappings.

Locally weighted regression corresponds to finding, for each kernel function $\Psi_i$, the weight vector $w_i$ which minimizes the quadratic error criterion:

$$J_i = \sum_{k=1}^{M} \Psi_i(k)\left(\theta(k) - w_i(k)\right)^2,$$

where the $k$'s are the $M$ discrete time steps. Following [18], [24], an on-line version of this learning process can be implemented using incremental regression, which is done with the use of recursive least squares with a forgetting factor of $\lambda$, to determine the weights $w_i$. Given the target data $\theta(t)$, $w_i$ is updated by:

$$
\begin{aligned}
w_i(k+1) &= w_i(k) + \Psi_i(k)P_i(k+1)\left(\theta(k) - w_i(k)\right), \\
P_i(k+1) &= \frac{1}{\lambda}\left(P_i(k) - \frac{P_i(k)^2}{\frac{\lambda}{\Psi_i(k)} + P_i(k)}\right), \qquad (7)
\end{aligned}
$$

where $P$ is the inverse covariance matrix [25]. If $\lambda < 1$, the regression gives more weight to recent data.

Fig. 2 shows an example of the filtering capacity of the presented methods. As anticipated, a pool of 3 oscillators (actually 2 oscillators and 1 integrator) is too small for doing proper filtering, mainly during the stance phase (dwell intervals). In contrast, the two other methods perform equally well, one with 11 oscillators, and the other with 3 oscillators and a kernel filter. This is this later method which was implemented in this paper. Interestingly, the figure confirms that there is no delay, on average, between the input signal and the filter output.

*4) Coupling between different joints:* So far, we explained how to use adaptive oscillators to get an on-line estimate of a filtered single input. However, in walking several joints are involved, and are supposed to move at the same global frequency. Therefore, by copying the above-mentioned system to each of the joint, the global convergence of the system frequency can be enhanced by forcing the different oscillators to reach a consensus. For example, the frequency equation in (5) can be replaced by:

$$\dot{\omega}_j(t) = \nu \sum_{j=1}^{J} F_j(t)\cos\phi_{1,j}(t)/J, \qquad (8)$$

where $J$ is the number of independent joints involved in the task. Similarly, amplitudes could be coupled among the two symmetrical (left and right) joints, since they are supposed to follow the same periodic profile.

*5) Assistance:* Finally, to provide assistance without relying on an inverse dynamical model of the body (as done in [12], [13]), we adopted the following approach. First, the system presented above was used to provide an estimate of the joint(s) position in the future. Indeed, recomputing (6) by replacing $\phi(t)$ by $\phi(t) + \Delta_\phi$, provides an estimate of what the joint position *should* be at a time corresponding to a $\Delta_\phi$ phase lead in the future:

$$
\begin{aligned}
\hat{\theta}_{\star,\Delta}(t) &= \frac{\sum \Psi_{i,\Delta}(\phi_1(t))w_i}{\sum \Psi_{i,\Delta}(\phi_1(t))}, \qquad (9) \\
\Psi_{i,\Delta}(\phi(t)) &= \exp\left(h(\cos(\phi(t) + \Delta_\phi - c_i) - 1)\right).
\end{aligned}
$$

Second, this estimated future position $\hat{\theta}_{\star,\Delta}(t)$ can be used to attract the user's joint in a force field:

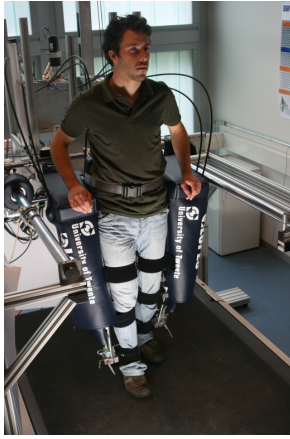$$\tau_{ref}(t) = k_f\left(\hat{\theta}_{\star,\Delta}(t) - \theta(t)\right), \qquad (10)$$

Fig. 3. Picture of an healthy subject wearing the LOPES.

where $k_f$ is the field stiffness and $\tau_{ref}(t)$ the desired torque to be applied by the assistive device.

In sum, the method of assistance we implemented here is aiming at continuously attracting the user's joints to their own future (using the force field (9), (10)), but leaving the opportunity to the user to constantly adapt the frequency (through the adaptive oscillator (5)) and shape (through the filter (7)) of this attractive pattern. For simplicity, we used a constant stiffness $k_f$ and no damping in the force field (10).

### B. Participants

Nine healthy participants took part in the experiment (aged 24-28, weight 58-86, four female, five male). None of them ever experienced the oscillator-based protocol we describe in this paper before the actual acquisition. All participants were volunteers and signed an informed consent form.

### C. Assistive device and experimental setup

For testing our approach, we used the LOPES (see Fig. 3)), a treadmill-based lower-limb exoskeleton developed at the University of Twente [9], [19]–[21], and capable of assisting 8 DOFs of the lower-limbs (right and left hip abduction/adduction, hip flexion/extension, and knee flexion/extension, forward/backward and sideways movements of the pelvis) by providing torques through the principle of series elastic actuator [21], [26]. The LOPES is lightweight and actuation is produced remotely by means of Bowden cables. Therefore, it is considered as a close-to-transparent device, inducing only small changes in the kinematic and EMG patterns with respect to normal walking [20].

The joints kinematics was recorded using the LOPES sensors, both to feed the adaptive oscillators, and to proceed with post-hoc analyses. The LOPES was controlled using Matlab (the MatWorks, Natick, MA), with a sampling time of 1ms.

The energy expenditure was measured by the Oxycon Pro system (Jaeger, Hoechberg, Germany). Subjects were connected to the Oxycon with a flexible tube making an airtight seal to a facemask, measuring oxygen consumption ($V_{O_2}$) and the volume expiration ($V_E$). Every five seconds (0.2Hz) these parameters were measured and stored on the personal computer connected to the Oxycon.

### D. Experimental protocol

The participant comfortably walked on the treadmill, wearing the LOPES on both legs, except during the "free walking" condition, detailed later. The LOPES was fastened via attachment cuffs to the middle of the thighs, and the top and bottom of the calves (see Figure 3). The LOPES pelvis module was further attached to the participant belly with a belt. Participants were asked to walk comfortably with a treadmill speed of 3.6km/h.

This study focused on assistance in the sagittal plane, and we decided to assist only the hips during walking. To improve the LOPES transparency, a force proportional to the joints' speed was applied to the hips and knees to compensate for the friction induced by the exoskeleton's joints.

Each participant underwent four types of condition, in a randomized order:

1) In the "free walking" condition, participants walked on the treadmill without wearing the LOPES. This condition lasted a single trial of about 6 minutes, and was used to evaluate the level of expended energy during normal walking.

2) In the "transparent" condition, the LOPES was controlled to be as transparent as possible, i.e. by setting $k_f = 0$ in (10), for each joint. This condition lasted a single trial of about 6 minutes, and was used to evaluate the actual level of transparency of the LOPES on gait cadence and energy consumption.

3) In the "low assistance" condition, participants received an assitance of $k_f = 0.0142W$ Nm/deg at the hips, where $W$ is the participant's total body weight. This condition was made of two trials: the first one lasted about 6 minutes at a constant treadmill speed, and the second one lasted about 12 minutes with treadmill speed variations. The second trial will not be analyzed here due to space constraints.

4) In the "high assistance" condition, participants received an assitance of $k_f = 0.0284W$ Nm/deg at the hips. This condition was also made of two trials being 6 and 12 minutes long, and keeping only the first one for this paper.

Note that the two levels of assistance were calculated based on pilot results, to provide, on average, an absolute assisitive torque corresponding to 50% and 100% of the average absolute torque produced by the hip during walking, as reported in [28]. This paper reports data corresponding only to steady-state behavior, such that we kept only the last 2 minutes of the 6 minutes long trials in the database.

For setting up the filter and the assistive algorithm, we used the following parameters: for the adaptive oscillator: $\nu = 6$, $\eta = 0.25$, $K = 6$, and full coupling between the estimated frequencies and amplitudes; for the non-linear filter: $\lambda = 0.9999$, $N = 90$, and $h = 144$; and for the predictor: $\Delta_\phi = 36°$ (10% of the cycle).

## E. Data analysis and statistics

To display the movement kinematics, the actual angular position signals recorded by the LOPES were off-line low-pass filtered (Butterworth, forward and backward in time, 3rd order, cut-off frequency of 10Hz).

The following variables were computed for statistics:

- The *average absolute error* between the estimation of the angular position in the future, delayed by the amount of time anticipation, and the actual position, i.e.:

$$\overline{\left| \hat{\theta}_{\star,\Delta} \left( t + \frac{\Delta_\phi}{\omega(t)} \right) - \theta(t) \right|}_t. \qquad (11)$$

- Two kinematics landmarks, namely the hips and knees *displacement range* (difference between maximum and minimum position) and the *cycle duration*. These were computed for each cycle, then averaged per condition and participant. The cycle duration was computed from gait events that were extracted from COP movements recorded by a force plate bellow the treadmill, and was therefore also available in the "free walking" condition.

- The *normalized expended energy*, which was inferred from the formula used in [27]:

$$\bar{E}[\text{kJ/kg}] = \frac{16.58 V_{O_2} + 4.51 V_{CO_2}}{W}, \qquad (12)$$

where $V_{O_2}$ and $V_{CO_2}$ are the volumes of $O_2$ and $CO_2$ involved in respiratory exchange.

When appropriate, post-hoc comparisons of the ANOVA levels were tested using the Tukey-Kramer method. All data processing and statistics were computed using Matlab, and with a $p$ factor of 0.05.

## III. Results

### A. Oscillator predictive capacity

The oscillator predictive capacity proved to be very good, the average absolute error computed in (11) being below $1.5°$ for each participant, leg, and condition. A 2-factor (leg×condition) repeated measures ANOVA revealed significance for the condition factor only: the predictions tended to be a bit more accurate when assistance was provided ($k_f > 0$).

### B. Kinematics variables

The angular kinematic profiles are shown in Fig. 4 for the right leg (they are very similar, but with a phase-shift of $50\%$, for the left one). The figure shows that, when assistance was delivered, the movements tended to be more ample, even for the knee (which was never assisted). This was confirmed by repeated measures ANOVAs: for the hip, the displacement range significantly depended on the condition, but neither on the leg nor on the interaction between the two factors. For the knee, it depended both on the condition and on the leg (the left knee did slightly larger movements), but not on their interaction. Regarding the cycle duration, the participants also tended to change this parameter as a function of the recieved assistance. In both the "free walking" and "transparent" conditions, the mean cycle duration was around
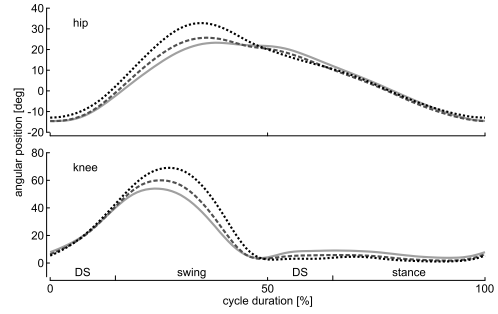


Fig. 4. Angular trajectory of the right hip (top) and knee (bottom) during the "transparent" condition (solid light gray), the "low assistance" condition (dashed dark gray), and the "high assistance" condition (dotted black). Labels show the periods of double support (DS), swing, and single support stance. Averaged across participants.
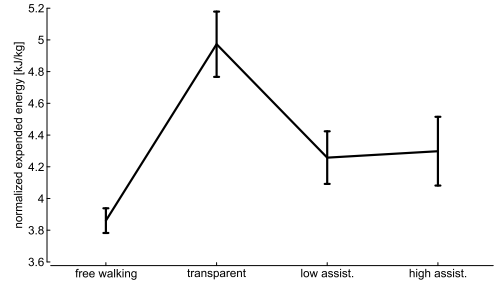


Fig. 5. Normalized expended energy by the participants during the different conditions. Error bars represent the standard error of the mean.

1.24s. In the "low assitance" condition, it dropped around 1.2s, to eventually reach 1.14s in the "high assitance" condition. Repeated measures ANOVA reached significance, with post-hoc tests establishing a significant difference between the "high assitance" condition and the two unassisted conditions.

In sum, as the assistance increased, the participants did larger movements, and increased the walking cadence.

Finally, we computed the metabolic energy consumption, from (12). Fig. 5 shows this result. First, it is visible that the supposedly transparent exoskeleton actually significantly loaded the participants, since the expended energy increased from the "free walking" to the "transparent" condition. Second, the figure establishes the efficiency of the assistance, since the expended energy decreased again for the two assisted conditions, to about two thirds of the difference with the "free walking" condition. The repeated measures ANOVA confirmed the significance of this modulation, and post-hoc tests revealed significant pairwise differences only between the "transparent" condition and any of the others.

## IV. Discussion and Conclusion

In this paper, we presented an extension of our previous work about using oscillator-based controller to assist rhythmic movements. In particular, we focused on walking assistance, using the LOPES exoskeleton. We derived a model-free version of our approach, whose principle is to attract the user's joints "to their own future", this attractor being constantly adapted to movement changes. Our results first

established that there were significant changes in the gait pattern depending whether the participant was assisted or not. A possible explanation to this behavior is that the assistance method — which is based on dynamical interactions between the user and the device — changed the resonance frequency of the coupled system, therefore attracting the user to a new cadence [29] and a different pattern [28].

More interestingly, we also showed that our assistance was capable of actually supporting the user, since the energy expended during the task decreased significantly. However, we only managed to reach a level slightly above the one during free walking, such that benefit of our assistance was completely washed out by the burden of wearing the device. Possible directions to improve this result would require to (i) make the LOPES more transparent, (ii) increase the level of assistance (although Fig. 5 already shows a kind of saturation), and (iii) give longer familiarization trials to the users. All in all, we think that this result is encouraging, given the challenge related to reduce the metabolic cost of free walking with an assistive device, as reported in the literature [11], [30].

In conclusion, we think that these results support our approach of designing new protocols for rehabilitation and assistance based on primitives, namely oscillators in the case of rhythmic movements. Ideally, this framework could be adapted to a lot of situations, due to the intrinsic flexibility of dynamical systems. In the future, we will explore the adaptation of this framework to rehabilitation protocols, targeting the needs of specific patients.

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