Article de périodique (Journal article)

"Real-time estimate of period derivatives using adaptive oscillators: Application to impedance-based walking assistance"

Ronsse, Renaud ; De Rossi, Stefano Marco Maria ; Vitiello, Nicola ; Lenzi, Tommaso ; Koopman, Bram ; van der Kooij, Herman ; Carrozza, Maria Chiara ; Ijspeert, Auke Jan

Abstract

Inferring temporal derivatives (like velocity and acceleration) from a noisy position signal is a well-known challenge in control engineering, due to the intrinsic trade-off between noise filtering and estimation bandwidth. To tackle this problem, in this paper we propose a new approach specifically designed for periodic movements. This approach uses an adaptive oscillator as fundamental building block. It is a tool capable of synchronizing to a periodic input while learning its features (frequency, amplitude, ...) in dedicated state variables. Since the oscillator's input and output are perfectly synchronized during steady-state regime, a non-delayed estimate of the input temporal derivatives can be obtained simply by deriving the output analytical form. Pending a (quasi-)periodic input signal, these temporal derivatives are thus synchronized with the actual kinematics, while the signal bandwidth can be arbitrarily tuned by the intrinsic dynamics of the oscillator. We further validate this approach by developing an impedance-based strategy for assisting human walking in the LOPES lowe[...]

Référence bibliographique

Ronsse, Renaud ; De Rossi, Stefano Marco Maria ; Vitiello, Nicola ; Lenzi, Tommaso ; Koopman, Bram ; et al. *Real-time estimate of period derivatives using adaptive oscillators: Application to impedance-based walking assistance*. In: *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, Vol. 0, no.0, p. 3362-3368 (7-12 Oct 2012)

DOI : 10.1109/IROS.2012.6385702

Real-time Estimate of Period Derivatives using Adaptive Oscillators: Application to Impedance-Based Walking Assistance*

Renaud Ronsse[1], Stefano Marco Maria De Rossi[2], Nicola Vitiello[2], Tommaso Lenzi[2], Bram Koopman[3]
Herman van der Kooij[3], Maria Chiara Carrozza[2], and Auke J. Ijspeert[4]

Abstract*— Inferring temporal derivatives (like velocity and acceleration) from a noisy position signal is a well-known challenge in control engineering, due to the intrinsic trade-off between noise filtering and estimation bandwidth. To tackle this problem, in this paper we propose a new approach specifically designed for periodic movements. This approach uses an adaptive oscillator as fundamental building block. It is a tool capable of synchronizing to a periodic input while learning its features (frequency, amplitude, ...) in dedicated state variables. Since the oscillator's input and output are perfectly synchronized during steady-state regime, a non-delayed estimate of the input temporal derivatives can be obtained simply by deriving the output analytical form. Pending a (quasi-)periodic input signal, these temporal derivatives are thus synchronized with the actual kinematics, while the signal bandwidth can be arbitrarily tuned by the intrinsic dynamics of the oscillator. We further validate this approach by developing an impedance-based strategy for assisting human walking in the LOPES lower-limb exoskeleton. Preliminary results with a single participant give rise to three main conclusions. First, our method indeed provides velocity and acceleration estimates of the participant's joint kinematics which are smoother and less delayed with respect to the actual kinematics than using a standard Kalman filter. Second, closing the human-robot loop with a high-gain impedance field depending on the acceleration is not possible with a Kalman filter approach, due to unstable dynamics. In contrast, our approach tolerates high gains (up to 70% of the nominal walking torque), showing its intrinsic stability. Finally, no clear benefit of the acceleration-dependent field with respect to a simpler position-dependent field is visible regarding the reduction of metabolic cost. This last result illustrates the challenge of designing sound assistive strategies for complex tasks like walking.

I. INTRODUCTION

Measuring a position signal with a digital encoder is intrinsically noisy, due to quantization errors and some irregularities of the space between two consecutive encoder slits. Furthermore, many applications require to infer an estimate of the temporal derivatives of this measured position, in particular velocity and acceleration. Using specific velocity and/or acceleration sensors impacts on the device cost, complexity, and encumbrance, while the corresponding signal processing becomes challenging [1]. A more common alternative is to infer velocity and acceleration directly from the noisy position signal. An abundant literature exists to propose smart signal processing techniques to tackle this problem.

In this paper, we propose a novel approach to estimate the velocity and acceleration (and potentially higher-order derivatives) of a noisy position signal by using adaptive oscillators. Adaptive oscillators are mathematical tools developed by Righetti et al. [2], [3] and used in various applications [4]: adaptive control of compliant robots, frequency analysis, and construction of limit cycles of arbitrary shape. More recently, we used them in robotics for movement assistance [5]–[8] and predictive control [9], [10]. An adaptive oscillator is able to synchronize to an input signal by learning its features (frequency and amplitude/envelope) in dedicated state variables. As such, estimates of temporal derivatives can be obtained from analytical expressions of the estimated signal envelope. This approach works thus only for cyclical (or periodic) signals close to steady-state regime, but combines the nice advantages of filtering out the measurement noise (through the dynamics of the adaptive oscillator) and of giving estimates which are, at steady state, phase-synchronized (i.e. delay-free) with respect to the actual temporal derivatives [3]. This is a critical difference between this approach and classical low-pass filtering, which unavoidably introduces delay.

This papers is organized as follows. In Section II, we briefly review the state-of-the-art for estimating velocity and acceleration from a noisy position signal. In Section III, we propose our new oscillator-based approach. In Section IV, we apply this technique to an assistive strategy for human walking, by using the LOPES device [11]–[14]. This assistance is based on a so-called impedance control law, requiring therefore an estimate of velocity and acceleration to be properly implemented. Section V discusses the main results of this experiment, and the paper ends with a conclusion.

*This work was partly supported by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreements num. 231451 (EVRYON) and 287894 (CYBERLEGs); and by an internationalization grant from UCLouvain awarded to RR (IMMC11/13).

[1]R. Ronsse is with the Centre for Research in Mechatronics, Institute of Mechanics, Materials and Civil Engineering, Université catholique de Louvain, B-1348 Louvain-la-Neuve, Belgium. renaud.ronsse@uclouvain.be

[2]S.M.M. De Rossi, N. Vitiello, T. Lenzi, and M.C. Carrozza are with the BioRobotics Institute, Scuola Superiore Sant'Anna, 56025 Pontedera (Pi), Italy. {s.derossi,n.vitiello,t.lenzi,carrozza}@sssup.it

[3]B. Koopman and H. van der Kooij are with the Biomechanical Engineering Laboratory, Institute for Biomedical Technology and Technical Medicine (MIRA), University of Twente, 7500 EA Enschede, The Netherlands. {B.Koopman,H.vanderKooij}@ctw.utwente.nl

[4]A.J. Ijspeert is with the Biorobotics Laboratory, Institute of Bioengineering, École Polytechnique Fédérale de Lausanne (EPFL), 1015 Lausanne, Switzerland. auke.ijspeert@epfl.ch

II. ESTIMATING DERIVATIVES OF POSITION

This section briefly reviews the existing methods to estimate the temporal derivatives (velocity and acceleration) of a position signal provided e.g. by a digital encoder.

Existing methods for estimating the time derivatives of an encoder signal range in two categories, depending whether a model of the system dynamics is available or not. Model-based approaches require a full dynamic model of the system in order to combine the system's inputs and outputs with dynamic predictions. Typical approaches include model-based Kalman filters [15], neural networks [16] or other nonlinear methods [17], [18]. Model-based approaches can provide accurate estimates of derivatives, but are strongly context-dependent, such that their performances significantly rely on the accuracy of the process model.

Model-free methods, conversely, do not make use of dynamic models of the system, and only rely on data-processing algorithms. The naive way to obtain a velocity estimate of an input signal is through a digital, filtered derivative estimation. This approach suffers from the well-know trade-off between bandwidth and smoothness [19]: The smoother the estimate, the higher the time (or phase) delay introduced by the filter. Most non-naive approaches can be divided into three main categories [20]: (i) Predictive post-filtering techniques, (ii) linear state space observers, and (iii) indirect methods interpolating the data before performing an exact (continuous) derivative evaluation.

Predictive post-filtering techniques perform a (usually delay-free) filtering on the numerically differentiated signal. Most common approaches are summarized in [21] and include Taylor series expansion, backwards difference expansion, and least squares fitting. All these techniques provide a predictive filtering of the past signal, and then estimate the signal slope based on its derivative. A more recent approach using an adaptive windowing of the signal was proposed in [22] and showed to be superior to traditional filtering techniques. Importantly, these techniques were developed to get only an estimate of the first order derivative (i.e. velocity), and are not appropriate when the estimate of the acceleration is also required.

State space observers use a linear, time-invariant model as a representation of data and its derivatives. The most common of these approaches is the model-free linear Kalman filter technique [1]. In this case, the process is modeled as a noise-driven chain of n integrators for which an observer can be constructed. It provides an estimate of the position and its $(n-1)$ first derivatives by using a n-equations system, the variability of intrinsic noise being the sole open parameter. A more recent implementation, based on an extended Kalman filter taking the encoder quantization into account, was proposed in [23]. Other state-space techniques were proposed in [24], [25]. The approach proposed by [26] is also worth being mentioned, because it specifically targets periodic signals. It is however practically more difficult to implement than the method presented here, due to the huge number of open parameters, requiring a partial knowledge of the input frequency content.

Finally, indirect methods are based on the approximation of the signal using interpolation, and analytical differentiation of this interpolation to get the derivative estimates. Polynomial interpolation approaches were first presented in [27]. Recently some authors proposed techniques to skip some recorded encoder events which do not increase the precision of the estimate (e.g. [20]). This turns the time stamping approach effectively applicable to real-world scenarios, for estimation of both velocity and acceleration.

III. PROPOSED APPROACH

This section introduces a new method to get a non-delayed estimate of the velocity and acceleration (and potentially higher-order derivatives) of a position signal. Importantly, this method is specifically tailored to work with periodic position signals, and relies on a central element, namely an adaptive oscillator.

A. Adaptive oscillator

The central element of the estimation method presented in this paper is an adaptive oscillator [2], [3]. Here, we introduce the simplest adaptive oscillator, which can be viewed as an augmented phase oscillator:

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

$$\dot{\omega}(t) = \nu F(t)\cos\phi(t), \tag{2}$$

where $\phi(t)$ is the oscillator phase, $\omega(t)$ its frequency, and ν the learning parameter determining the speed of phase synchronization to the periodic teaching signal $F(t)$. Note that in (2), the oscillator frequency is a state variable, integrating the phase update, in order to *learn* the frequency of the teaching signal $F(t)$, instead of doing mere synchronization only. As such, the oscillator has the capacity to constantly adapt its frequency to the teaching signal frequency, and to keep this input frequency in memory, i.e. in the state variable $\omega(t)$. The proof of convergence of $\omega(t)$ toward a stationary frequency was established by [2], while [3] provided further results with time-varying parameters.

The same authors further proposed to put several of these oscillators in parallel in a feedback loop (see the upper part of Fig. 1) to learn the features (i.e. the frequency spectrum) of an arbitrary periodic input $\theta(t)$ [28]. Assuming the signal to be periodic (such that all frequencies with a non-zero power spectrum are multiple of a fundamental harmonic), an estimate of the input signal can be derived from its Fourier decomposition (see also [29]):

$$\hat{\theta}(t) = \sum_{i=0}^{K} \alpha_i \sin(\phi_i(t)) = \sum_{i=0}^{K} \alpha_i \sin(i\omega t + \varphi_i), \tag{3}$$

where K denotes the number of harmonics kept in the estimate. Righetti et al. [28] showed that the convergence of $\hat{\theta}(t)$ to $\theta(t)$ is guaranteed by using the difference between these two signals as teaching signal: $F(t) = \theta(t) - \hat{\theta}(t)$, and by implementing the following integrators for learning the harmonics amplitude:

$$\dot{\alpha}_i(t) = \eta F(t)\sin\phi_i(t), \tag{4}$$

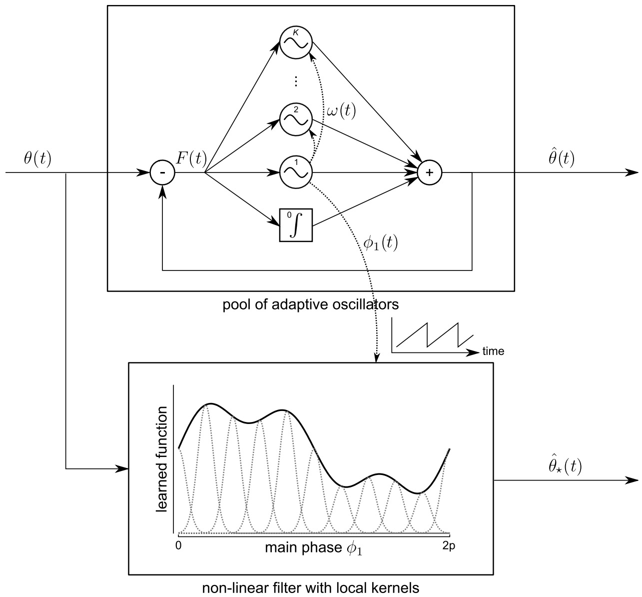

Fig. 1. On-line learning of a periodic but non-sinusoidal input signal $\theta(t)$. The upper block is a pool of adaptive oscillators (4), (5), decomposing the input into a real-time Fourier series. The lower block is a kernel-based non-linear filter, mapping the phase of the main harmonic $\phi_1(t)$ to the input envelope. Adapted from [30].

where η is the integrator gain. Similarly, the learning of the phases and frequency is governed by extensions of (1) and (2), respectively:

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

Note that in (4), and (5), the 0-th oscillator ($i=0$) is a simple integrator (assuming $\phi_0(0)=\pi/2$) learning the signal offset, i.e. $\dot{\alpha}_0(t)=\eta F(t)$. From (4), and (5), it is visible that steady-state is reached when $F(t)=0$, i.e. when $\hat{\theta}(t)=\theta(t)$. If $\theta(t)$ is only quasi-stationary — i.e. if the input features (frequency, amplitudes, phases) slowly vary in time — $\hat{\theta}(t)$ will be a low-pass filtered version of $\theta(t)$. Indeed, random noise affecting the input $\theta(t)$ will be filtered out by the dynamics of the adaptive oscillator (4), (5). Importantly, $\hat{\theta}(t)$ and $\theta(t)$ will however be phase-synchronized on average [3].

B. Estimating derivatives using adaptive oscillator

If the estimated features (namely ω, α_i, φ_i) converged to the actual ones, an estimate of the input's derivatives can be obtained by differentiating the analytical form of the position estimate, i.e. (3). For the velocity and acceleration, this gives:

$$\begin{aligned} \hat{\dot{\theta}}(t) &= \sum_{i=1}^{K} \alpha_i(t) i\omega(t)\cos\phi_i(t), \\ \hat{\ddot{\theta}}(t) &= \sum_{i=1}^{K} -\alpha_i(t)(i\omega(t))^2\sin\phi_i(t). \end{aligned} \tag{6}$$

Again in steady-state (i.e. if the features are stationary and the estimations converged), these filtered estimates are undelayed with respect to the actual signals, in contrast to more classical low-pass filter-based approaches like Kalman filtering.

In [6], we used this approach to estimate the velocity and acceleration of human quasi-sinusoidal elbow movements — i.e. by limiting (3) and (6) to the first harmonic ($K=1$) — and to provide assistance based on an inverse dynamic model.

C. Kernel-based filter

If the input signal $\theta(t)$ possesses a large frequency spectrum, like for instance if it contains a plateau of quasi-constant position, the estimated signal $\hat{\theta}(t)$ can only merely approximate the original one, since the learned signal is truncated to a finite number of harmonics K. Moreover, this approximation error grows up with higher-order time derivatives, each amplifying high frequencies by a factor ω.

To solve this limitation by keeping K reasonably low, we propose to augment the structure of the learning algorithm with a second block, working in the time (or phase) domain [30]. The approach is described in Figure 1. The pool of adaptive oscillators is used only to extract the *phase* of the input signal. i.e. $\phi_1(t)$. This phase is used afterwards as the input of a non-linear filter working in the phase domain.

This filter actually solves a supervised learning problem, where the signal to be learned is approximated as a sum of local models, i.e.:

$$\hat{\theta}_\star(t) = \frac{\sum \Psi_i(t) w_i}{\sum \Psi_i(t)}, \tag{7}$$

where $\Psi_i(t) = \exp\left(h(\cos(\phi(t)-c_i)-1)\right)$ is a set of N Gaussian-like kernel functions, and $\sum$ stands for $\sum_{i=1}^{N}$. The parameter h determines the kernel width, and $c_i = \bar{c} + i2\pi/N$ their center (equally spaced between 0 and 2π in N steps). These kernel functions are represented by the dotted gray curves in Figure 1. Locally weighted regression corresponds to finding, for each kernel function Ψ_i, the weight vector w_i which minimizes a quadratic error criterion. Following [30], [31], 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 λ, to determine the weights w_i. Given the input $\theta(t)$, w_i is updated by:

$$\begin{aligned} w_i(t_{k+1}) &= w_i(t_k) + \Psi_i(t_k)P_i(t_{k+1})\left(\theta(t_k) - w_i(t_k)\right), \\ P_i(t_{k+1}) &= \frac{1}{\lambda}\left(P_i(t_k) - \frac{P_i(t_k)^2}{\frac{\lambda}{\Psi_i(t_k)} + P_i(t_k)}\right), \end{aligned} \tag{8}$$

where the t_k's are the discrete time steps, and P is the inverse covariance matrix [32]. If $\lambda < 1$, the regression gives more weight to recent data.

An estimate of the temporal derivatives of $\theta(t)$ can again be obtained by differentiating equation (7). Assuming steady-state weights w_i, the first derivative gives:

$$\hat{\dot{\theta}}_\star(t) = \frac{(\sum \Psi_i(t))(\sum \dot{\Psi}_i(t) w_i) - (\sum \dot{\Psi}_i(t))(\sum \Psi_i(t) w_i)}{(\sum \Psi_i(t))^2}, \tag{9}$$

where the kernel derivatives are given by:

$$\dot{\Psi}(t) = -\Psi(t) h \sin(\phi(t) - c_i)\omega(t). \tag{10}$$

Moreover, from (10), it can be observed that:

$$\sum_{i=1}^{N} \dot{\Psi}_i \simeq \frac{-Nh\omega}{2\pi} \int_0^{2\pi} \sin(\phi-\varphi) \exp\left(h(\cos(\phi-\varphi)-1)\right) d\varphi = 0.$$

This simplification holds if the number of kernels is large enough and/or if the kernels are wide enough. Then (9) simply reduces to:

$$\hat{\dot{\theta}}_\star(t) = \frac{\sum \dot{\Psi}_i(t) w_i}{\sum \Psi_i(t)}, \tag{11}$$

i.e. to a weighted sum of the derivatives of each local kernel. Similarly, estimates of temporal derivatives of any order j can be obtained from:

$$\widehat{\frac{d^j\theta_\star}{dt^j}}(t) = \frac{\sum \frac{d^j\Psi_i}{dt^j} w_i}{\sum \Psi_i}. \tag{12}$$

For acceleration, the second derivative of the local kernel is obtained from (10):

$$\ddot{\Psi}_i(t) = -\dot{\Psi}_i(t) h \sin(\phi(t)-c_i)\omega(t) - \Psi_i(t) h \cos(\phi(t)-c_i)\omega(t)^2 \underbrace{-\Psi_i h \sin(\phi(t)-c_i)\dot{\omega}(t)}_{\simeq 0}. \tag{13}$$

The last term vanishes assuming that the main frequency ω evolves at a slower timescale than the kernel functions.

IV. IMPEDANCE-BASED WALKING ASSISTANCE

In this section, we validate the estimation method previously presented with an experimental investigation. Numerical parameters used for this experiment are: $\nu = 6$, $\eta = 0.25$, $K = 6$, $h = 36$, $\lambda = 0.9995$, and $N = 90$.

A. Assistive strategy

The goal of this experiment is to provide assistance during walking by means of a lower-limb exoskeleton (the LOPES device, see below). The implemented control approach requires to deliver a torque to human joints which obeys a so-called impedance law:

$$\tau_e(t) = k_f W \left(k_c + k_p \hat{\theta}_\star(t) + k_a \hat{\ddot{\theta}}_\star(t)\right), \tag{14}$$

where k_p and k_a are gains making the assistive torque proportional to the joint position and acceleration, respectively (for simplicity, we did not include a term proportional to velocity); k_c is a constant gain; W is the participant weight; and k_f is the general modulation gain. The gain vector (k_c,k_p,k_a) is optimized (with $k_f = 1$) to minimize the squared error between the assistive torque $\tau_e(t)$ and the actual torque provided by human joints during steady-state walking, with the corresponding joint kinematics. These data were taken from [33]. It draws a parallel between our approach and other approaches providing assistance by computing the actual torque provided by the human using an inverse dynamic model [5], [6], [34]. In that respect, note that the vector (k_c,k_p,k_a) was separately optimized for the stance and swing phases, since they both obey largely different dynamics, and the respective fits were mixed during the double support phase.

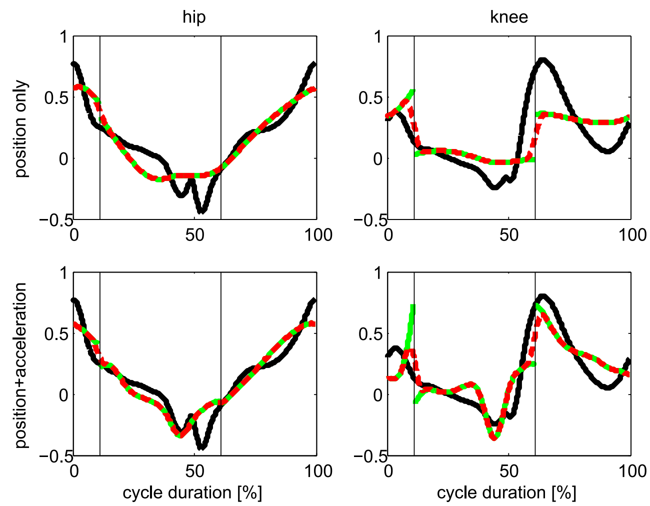

Fig. 2. Best fit of the gains in Equation (14) to match the human torques (normalized to the body weight, i.e. in Nm/kg) in the "position only" (top) and "position+acceleration" (bottom) conditions, for the hip (left) and knee (right) joints. Panels show the reference data (black), the optimization performed on the two subregions separately (green) and the mix of the two optimizations, modulated by the force plate data during the double support phase (dashed red). The swing phase takes place between the two vertical lines (from about 20% to about 50% of the gait cycle). Data taken from [33].

We performed this optimization on the hip and knee data (i.e. the two joints which can be assisted with the LOPES) and with 2 different configurations: position only ($k_a = 0$), and position+acceleration. The best fits are shown in Figure 2. For the hip, the behavior is strongly influenced by the position, such that adding the acceleration dependence does not really improve the fit. The torque is proportional to the joint position, with a negative gain (i.e. in anti-phase). Furthermore, the gains are quite similar between subregions 1 and 2 (swing and stance phases), making the transition very smooth. For the knee, a torque also proportional to the acceleration provides a better fit. The "position+acceleration" condition gives a good fit but induces a quite large negative peak at the end of the swing phase. The gains are smaller during the swing phase, since the knee follows almost a ballistic trajectory during that phase (no actuation torque).

B. Experimental protocol

A single participant took part to the preliminary experiment described here (age 26, male). The experiment was conducted in agreement with the local institution's ethics regulations, and participant signed a written consent form. This participant was not part of the cohort of subjects who were involved in the experiment giving the walking data we used for curve fitting in Section IV-A [33].

We used the LOPES (Figure 3), a treadmill-based lower-limb exoskeleton developed at the University of Twente [11], [14], 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

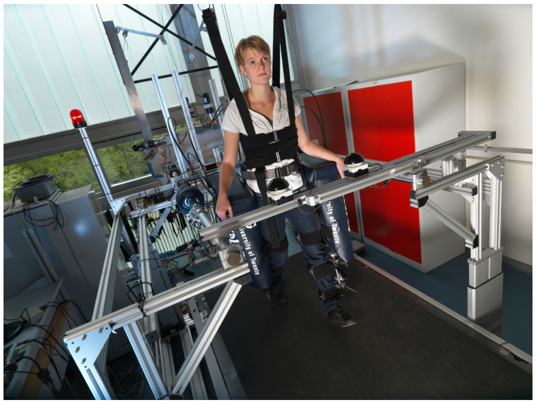

Fig. 3. Picture of an healthy subject wearing the LOPES.

movements of the pelvis) by providing torques through the principle of series elastic actuation [13], [35]. 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 [12]. To improve the LOPES transparency, we further used a model-based dynamic compensation, as described in [36], and using estimates of velocity and acceleration either provided by a Kalman filter, or by our new method, depending on the condition (see below).

The joint kinematics were recorded using the LOPES sensors, both to feed the adaptive oscillators, and to proceed with post-hoc analyses. The LOPES was controlled using Matlab/Simulink – xPC-Target (the Mathworks, Natick, MA), with a sampling frequency of 1kHz.

The metabolic energy expended by the participant was measured by the Oxycon Pro system (Jaeger, Hoechberg, Germany), measuring oxygen consumption (V_{O_2}) and the volume expiration (V_E). These parameters were measured and stored on the Oxycon at 0.2Hz. Thereafter, the *normalized rate of expended energy* was inferred from the formula used in [37]:

$$\bar{E}[\mathrm{W/kg}] = \frac{16.58\dot{V}_{O_2} + 4.51\dot{V}_{CO_2}}{W}, \tag{15}$$

where $\dot{V}_{O_2}$ and $\dot{V}_{CO_2}$ are the rates of O_2 and CO_2 volume involved in respiratory exchange, and W is the participant body weight.

The participant walked comfortably 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. The LOPES pelvis module was further attached to the participant waist with a belt.

The participant underwent eight types of condition, as detailed in Table I. These conditions implemented gradual levels of assistance: no assistance ($k_f = 0$), compensation of the exoskeleton dynamics, position-only impedance-based assistance ($k_a = 0$), and position+acceleration impedance-based assistance ($k_a \neq 0$). Most of these conditions were tested by using either a Kalman filter or our new oscillator-based approach to estimate velocity and acceleration. All assisted conditions used an assistance level of $k_f = 0.7$, such that the exoskeleton should provide 70% of the torque at the hips and knees during steady-state walking. All the conditions lasted a single trial of 6 minutes, with a treadmill speed of 3.6km/h. Only the last 2 minutes of each trial (steady-state walking) were used to compute the results.

TABLE I

EXPERIMENTAL CONDITIONS

Condition name	Q1	Q2	k_f	k_p	k_a	Q3
free-walk	No	No	0	0	0	-
zero-imp	Yes	No	0	0	0	-
transp-KF	Yes	Yes	0	0	0	KF
transp-AO	Yes	Yes	0	0	0	AO
pos-KF	Yes	Yes	0.7	$\neq 0$	0	KF
pos-AO	Yes	Yes	0.7	$\neq 0$	0	AO
posacc-KF	Yes	Yes	0.7	$\neq 0$	$\neq 0$	KF
posacc-AO	Yes	Yes	0.7	$\neq 0$	$\neq 0$	AO

Q1: In the LOPES? / Q2: Dynamic compensation? / Q3: method for estimating velocity and acceleration / KF: Kalman filter / AO: adaptive oscillator.

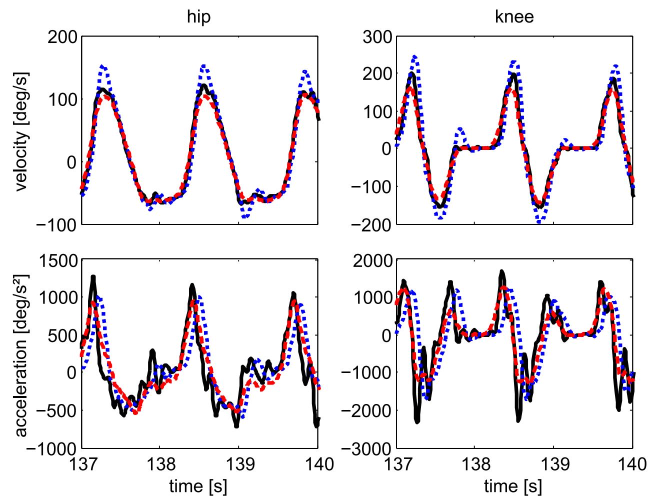

Fig. 4. Right hip and knee velocity and acceleration during 3 representative seconds of the "zero-imp" condition. Black: actual kinematics; Dotted blue: estimation provided by the Kalman filter; Dashed red: estimation provided by the adaptive oscillator.

V. RESULTS

First, Figure 4 compares the velocity and acceleration estimates provided by the Kalman filter and the oscillator-based approach presented here, for the right hip and knee, and during 3 representative seconds of the "zero-imp" condition. The velocity estimate provided both by the Kalman filter and by our oscillator-based approach are very close to the actual velocity (computed off-line), and the one provided by the oscillator-based method is smoother. This is confirmed by computing the mean absolute error over the whole trial duration (130s), showing a slight advantage in favor of the adaptive oscillator: 7.9 vs. 8.8deg/s for the hip, and 14.1 vs. 21.9deg/s for the knee. As expected, the Kalman-based acceleration estimate shows some delay with respect to the

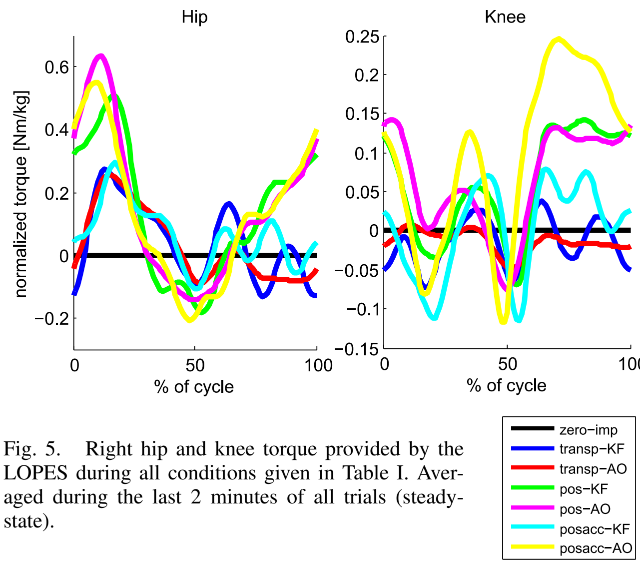

Fig. 5. Right hip and knee torque provided by the LOPES during all conditions given in Table I. Averaged during the last 2 minutes of all trials (steady-state).

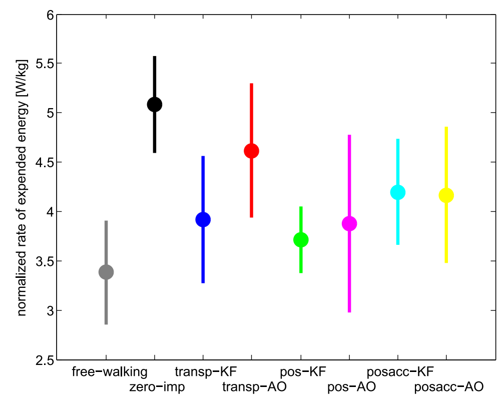

Fig. 6. Normalized rate of expended energy (Equation 15 during all conditions given in Table I. Mean ± STD during the last 2 minutes of all trials (steady-state).

actual acceleration, while the one provided by our method stays in phase with. This tendency is confirmed by computing the mean absolute error over the whole trial, clearly in favor of the adaptive-oscillator-based method: 168.4 vs. 224.6deg/s^2 for the hip, and 299.0 vs. 562.9deg/s^2 for the knee.

Figure 5 shows the torques provided by the LOPES during all conditions listed in Table I. Obviously, during the "zero-imp" condition, no torque was requested, since the LOPES was controlled to render zero impedance. During both "transp-XX" conditions, some torque was provided to cancel the exoskeleton dynamics, according to the method explained in [36]. Both conditions give rise to slightly different profiles, since the velocity and acceleration estimates were not exactly the same (see Figure 4). During both "pos-XX" conditions, some more torque was provided to assist walking. They are in good agreement with the upper panels of Figure 2 (up to a factor 0.7, since $k_f = 0.7$), again with some variations between the "pos-KF" and "pos-AO" conditions. The torque provided by the "pos-AO" condition was smoother, in agreement with the fact that the oscillator-based estimates were smoother than those provided by the Kalman filter. Finally, the "posacc-AO" also agrees with the lower panels of Figure 2 (position+acceleration). In contrast, the "posacc-KF" condition gave rise to big instabilities, putting the subject in a very uncomfortable situation. To cope with that, we had to reduce k_f as low as 0.15, such that the commanded torques approached those of the "transp-KF" condition (compare the dark and light blue curves).

Finally, Figure 6 shows the mean normalized rate of expended energy, i.e. the metabolic consumption, during the steady-state of the 8 different conditions. First, it is important to point out that the simple fact of wearing the LOPES (i.e. from "free-walk" to "zero-imp") caused a big increase of metabolic cost (in line with the results from [7], [8], obtained with 9 participants). This increase was partly compensated in the "transp-XX" conditions (mainly when the Kalman filter was used), but not to a point to conclude that the LOPES was actually transparent (in terms of metabolic cost) in these conditions. The lowest metabolic consumption was encountered in the "pos-XX" conditions, but, again, not to the point of reaching the baseline (free walking). The "posacc-XX" were apparently more challenging for the participant. This makes sense for the "posacc-KF", since in this case almost no assistance was provided, but is more unexpected for the "posacc-AO" condition. In sum, while wearing the LOPES caused an increase of energy expenditure of about 40%, two thirds of this increase were compensated by our most effective assistive strategies, corresponding to the "pos-XX" conditions. No clear difference between the oscillator-based and the Kalman-based approaches is observable in terms of energy expenditure.

VI. CONCLUSION

This paper provided a new method for getting a real-time estimate of the temporal derivatives (mainly velocity and acceleration) of noisy position signals, e.g. obtained through a digital encoder. This method works only for cyclical/periodic signals near to steady-state regime, but has the paramount advantage to provide estimates which are both filtered (i.e. the high-frequency, noise-driven part of the signal is filtered out), and delay-free (as opposed to classical low-pass filters). This is achieved by synchronizing the input signal to a (pool of) adaptive oscillator(s) — whose convergence is proved in [2], [3] — and a non-linear kernel filter in the phase domain.

This method was tested by implementing an impedance-based assistive control in the LOPES. Preliminary results obtained with a single participant illustrate that: (i) our method indeed provides velocity and acceleration estimates which are smoother and less delayed with respect to the actual kinematics than a standard Kalman filter; (ii) closing the loop with a high-gain impedance field depending on the acceleration is not possible with a Kalman filter approach, but well with our approach – illustrating therefore its intrinsic stability; and (iii) implementing an impedance-based assistive field which depends on the acceleration is not a trivial task, since no clear benefit with respect to a purely position-depended field was established, in terms of metabolic consumption. While our method seems to hold promise for the design of intrinsically stable impedance fields in human-robot rhythmic interactions, future work will have to specifically address the design of these complex interaction laws in order to optimize their efficiency.

References

[1] P. Belanger, P. Dobrovolny, A. Helmy, and X. Zhang, "Estimation of angular velocity and acceleration from shaft-encoder measurements," *Int J Robot Res*, vol. 17, no. 11, pp. 1225–1233, 1998.

[2] L. Righetti, J. Buchli, and A. J. Ijspeert, "Dynamic hebbian learning in adaptive frequency oscillators," *Physica D*, vol. 216, pp. 269–281, 2006.

[3] J. Buchli, L. Righetti, and A. J. Ijspeert, "Frequency analysis with coupled nonlinear oscillators," *Physica D*, vol. 237, pp. 1705–1718, 2008.

[4] L. Righetti, J. Buchli, and A. J. Ijspeert, "Adaptive frequency oscillators and applications," *The Open Cybernetics and Systemics Journal*, vol. 3, pp. 64–69, 2009.

[5] R. Ronsse, N. Vitiello, T. Lenzi, J. van den Kieboom, M. C. Carrozza, and A. J. Ijspeert, "Adaptive oscillators with human-in-the-loop: Proof of concept for assistance and rehabilitation," in *Biomedical Robotics and Biomechatronics (BioRob), 2010 3rd IEEE RAS and EMBS International Conference on*, 2010, pp. 668–674.

[6] ——, "Human-robot synchrony: Flexible assistance using adaptive oscillators," *IEEE Trans Biomed Eng*, vol. 58, no. 4, pp. 1001–1012, 2011.

[7] R. Ronsse, B. Koopman, N. Vitiello, T. Lenzi, S. M. M. De Rossi, J. van den Kieboom, E. van Asseldonk, M. C. Carrozza, H. van der Kooij, and A. J. Ijspeert, "Oscillator-based walking assistance: A model-free approach," in *Proc. IEEE Int Rehabilitation Robotics (ICORR) Conf*, 2011, pp. 1–6.

[8] 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, and A. J. Ijspeert, "Oscillator-based assistance of cyclical movements: model-based and model-free approaches." *Med Biol Eng Comput*, vol. 49, no. 10, pp. 1173–1185, Oct 2011.

[9] R. Ronsse, J. van den Kieboom, and A. J. Ijspeert, "Automatic resonance tuning and feedforward learning of biped walking using adaptive oscillators," in *Multibody Dynamics 2011, ECCOMAS Thematic Conference*, J.-C. Samin and P. Fisette, Eds., Brussels, Belgium, July 2011.

[10] W. van Dijk, B. Koopman, R. Ronsse, and H. van der Kooij, "Feed-forward support of human walking," in *Biomedical Robotics and Biomechatronics (BioRob), 2012 4th IEEE RAS and EMBS International Conference on*, 2012, pp. 1955–1960.

[11] J. F. Veneman, R. Kruidhof, E. E. G. Hekman, R. Ekkelenkamp, E. H. F. V. Asseldonk, and H. van der Kooij, "Design and evaluation of the lopes exoskeleton robot for interactive gait rehabilitation." *IEEE Trans Neural Syst Rehabil Eng*, vol. 15, no. 3, pp. 379–386, Sep 2007.

[12] E. H. F. van Asseldonk, J. F. Veneman, R. Ekkelenkamp, J. H. Buurke, F. C. T. van der Helm, and H. van der Kooij, "The effects on kinematics and muscle activity of walking in a robotic gait trainer during zero-force control," *IEEE Trans Neural Syst Rehabil Eng*, vol. 16, no. 4, pp. 360–370, 2008.

[13] H. Vallery, J. Veneman, E. van Asseldonk, R. Ekkelenkamp, M. Buss, and H. van Der Kooij, "Compliant actuation of rehabilitation robots," *IEEE Robot Autom Mag*, vol. 15, no. 3, pp. 60–69, Sep. 2008.

[14] H. Vallery, E. H. F. van Asseldonk, M. Buss, and H. van der Kooij, "Reference trajectory generation for rehabilitation robots: complementary limb motion estimation." *IEEE Trans Neural Syst Rehabil Eng*, vol. 17, no. 1, pp. 23–30, Feb 2009.

[15] M. Barut, S. Bogosyan, and M. Gokasan, "Speed-sensorless estimation for induction motors using extended kalman filters," *Industrial Electronics, IEEE Transactions on*, vol. 54, no. 1, pp. 272–280, 2007.

[16] S.-H. Kim, T.-S. Park, J.-Y. Yoo, and G.-T. Park, "Speed-sensorless vector control of an induction motor using neural network speed estimation," *Industrial Electronics, IEEE Transactions on*, vol. 48, no. 3, pp. 609–614, 2001.

[17] S. Nicosia and P. Tomei, "Robot control by using only joint position measurements," *Automatic Control, IEEE Transactions on*, vol. 35, no. 9, pp. 1058–1061, 1990.

[18] C. Canudas de Wit and N. Fixot, "Robot control via robust estimated state feedback," *Automatic Control, IEEE Transactions on*, vol. 36, no. 12, pp. 1497–1501, 1991.

[19] L. Bascetta, G. Magnani, and P. Rocco, "Velocity estimation: Assessing the performance of non-model-based techniques," *Control Systems Technology, IEEE Transactions on*, vol. 17, no. 2, pp. 424 –433, mar. 2009.

[20] R. Merry, M. van de Molengraft, and M. Steinbuch, "Velocity and acceleration estimation for optical incremental encoders," *Mechatronics*, vol. 20, no. 1, pp. 20–26, 2010, special Issue on "Servo Control for Data Storage and Precision Systems", from 17th IFAC World Congress 2008.

[21] R. H. Brown, S. C. Schneider, and M. G. Mulligan, "Analysis of algorithms for velocity estimation from discrete position versus time data," *Industrial Electronics, IEEE Transactions on*, vol. 39, no. 1, pp. 11–19, 1992.

[22] F. Janabi-Sharifi, V. Hayward, and C.-S. J. Chen, "Discrete-time adaptive windowing for velocity estimation," *Control Systems Technology, IEEE Transactions on*, vol. 8, no. 6, pp. 1003–1009, 2000.

[23] J. Corres and P. Gil, "Instantaneous speed and disturbance torque observer using nonlinearity cancellation of shaft encoder," in *Proc. IEEE 33rd Annual Power Electronics Specialists Conf. pesc 02*, vol. 2, 2002, pp. 540–545.

[24] L. Kovudhikulrungsri and T. Koseki, "Precise speed estimation from a low-resolution encoder by dual-sampling-rate observer," *IEEE/ASME Trans Mechatronics*, vol. 11, no. 6, pp. 661–670, 2006.

[25] Y. Su, C. Zheng, P. Mueller, and B. Duan, "A simple improved velocity estimation for low-speed regions based on position measurements only," *Control Systems Technology, IEEE Transactions on*, vol. 14, no. 5, pp. 937 –942, sep. 2006.

[26] R. Marino and G. Santosuosso, "Nonlinear observers of time derivatives from noisy measurements of periodic signals," in *Nonlinear control in the year 2000 volume 2*, ser. Lecture Notes in Control and Information Sciences, A. Isidori, F. Lamnabhi-Lagarrigue, and W. Respondek, Eds. Springer Berlin / Heidelberg, 2001, vol. 259, pp. 123–135.

[27] K. Saito, K. Kamiyama, T. Ohmae, and T. Matsuda, "A microprocessor-controlled speed regulator with instantaneous speed estimation for motor drives," *Industrial Electronics, IEEE Transactions on*, vol. 35, no. 1, pp. 95–99, 1988.

[28] L. Righetti and A. J. Ijspeert, "Programmable central pattern generators: an application to biped locomotion control," in *Proc. IEEE International Conference on Robotics and Automation ICRA 2006*, May 15–19, 2006, pp. 1585–1590.

[29] T. Petrič, A. Gams, A. J. Ijspeert, and L. Žlajpah, "On-line frequency adaptation and movement imitation for rhythmic robotic tasks," *The International Journal of Robotics Research*, vol. 30, no. 14, pp. 1775–1788, 2011.

[30] A. Gams, A. J. Ijspeert, S. Schaal, and J. Lenarčič, "On-line learning and modulation of periodic movements with nonlinear dynamical systems," *Autonomous Robots*, vol. 27, pp. 3–23, 2009.

[31] S. Schaal and C. G. Atkeson, "Constructive incremental learning from only local information," *Neural Comput*, vol. 10, no. 8, pp. 2047–2084, Nov 1998.

[32] L. Ljung and T. Söderström, *Theory and Practice of Recursive Identification*, ser. The MIT Press Signal Processing, Optimization, and Control Series, A. S. Willsky, Ed. Cambridge, Massachusetts: The MIT Press, 1983.

[33] B. Koopman and W. van Dijk, "Basic gait kinematics: reference data of normal subjects," University of Twente, Experimental data, 2010.

[34] H. Kazerooni, A. Chu, and R. Steger, "That which does not stabilize, will only make us stronger," *Int J Rob Res*, vol. 26, no. 1, pp. 75–89, 2007.

[35] G. A. Pratt and M. M. Williamson, "Series elastic actuators," in *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems 95. 'Human Robot Interaction and Cooperative Robots'*, vol. 1, Aug. 5–9, 1995, pp. 399–406.

[36] B. Koopman, E. H. F. van Asseldonk, R. Ronsse, W. van Dijk, and H. van der Kooij, "Rendering potential wearable robot designs with the lopes gait trainer," in *Proc. IEEE Int Rehabilitation Robotics (ICORR) Conf*, 2011, pp. 1–6.

[37] J. M. Brockway, "Derivation of formulae used to calculate energy expenditure in man." *Hum Nutr Clin Nutr*, vol. 41, no. 6, pp. 463–471, Nov 1987.