

Adaptive Oscillators as Template for Modeling and Assisting Rhythmic Movements

Renaud Ronsse

Abstract—This paper overviews our recent efforts for promoting adaptive oscillators as template for modeling and assisting rhythmic movements. Adaptive oscillators are dynamical systems that can be viewed as the simplest possible model of a neural Central Pattern Generator, augmented with learning dynamics. Therefore, if coupled to a human user producing a rhythmic movement, such an adaptive oscillator can be used to govern the behavior of an assistive robot providing different kinds of rhythmic movement support, with or without energy injection, and both for the upper- and the lower-limb.

I. INTRODUCTION

Rhythmic movements are repetitive actions executed along a periodic pattern. Some of them like breathing, chewing, or crawling are part of the essential repertoire for the survival of primitive species. Consequently, researchers established that they form a fundamental class of movements — or primitive — that is phylogenetically older than more complex activities like discrete reaching to a target [1]. Spinal neural circuitry plays a ubiquitous role in the execution of rhythmic movements. In particular, Central Pattern Generators (CPGs) are thought to be the source of rhythmicity in the production of muscular activation patterns governing locomotion movements in mammals [2]. Our recent work in bipedal locomotion modeling further showed how CPGs can be ideally combined with spinal reflexes for producing robust, versatile, and energy-efficient walking patterns [3].

In this contribution, we specifically focus on a tool that we extensively used in the recent past to model, predict, and assist human rhythmic movements, namely adaptive oscillators (AOs). An AO can be viewed as a harmonic oscillator, i.e. the simplest model of a CPG, that is augmented with learning mechanisms in order to synchronize to an external signal. This general framework is pictured in Fig.1. The rest of this paper overviews how we adapted it to representative scenarios of locomotion and upper-limb assistance.

II. ADAPTIVE OSCILLATOR

An AO is a dynamical system building upon a simple harmonic oscillator, i.e. $\dot{\phi} = \omega$, where ϕ and ω are the oscillator phase and frequency, respectively. More precisely, this oscillator is augmented with learning terms [4] storing in dedicated state variables the features (i.e. the phase ϕ_r ,

This work was supported by the EU within the CYBERLEGsPlusPlus project (H2020-ICT-2016-1, Grant Agreement #731931), the Belgian F.R.S.-FNRS (Aspirant grant #16744574, FRIA grant F3/5/5-MCF/XH/FC-18101), and by the Foundation van Goethem Brichant.

R. Ronsse is with the Institute of Mechanics, Materials, and Civil Engineering, the Institute of Neuroscience, and Louvain Bionics, UCLouvain, Louvain-la-Neuve, Belgium (renaud.ronsse@uclouvain.be).

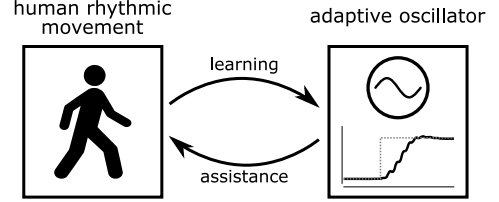


Fig. 1. General framework: An adaptive oscillator continuously learns the features of a rhythmic movements produced by a human, and in turns provides rhythmic assistance that is fine-tuned to the produced movement.

frequency ω_r , and amplitude α_r) of a quasi-rhythmic input signal, i.e. $x_r = \alpha_r \sin \phi_r$. Here, “quasi-rhythmic” should be understood in the sense that ω_r and α_r could be time-varying, yet at a slower timescale than the input frequency itself. The AO thus writes as:

$$\begin{aligned}\dot{\phi} &= \omega + \nu_\phi F / \alpha \cos \phi, \\ \dot{\omega} &= \nu_\omega F / \alpha \cos \phi, \\ \dot{\alpha} &= \eta F \sin \phi,\end{aligned}\tag{1}$$

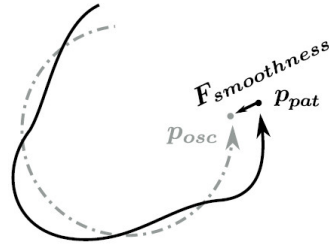
where ν_ϕ , ν_ω and η are gains driving the learning timescales [5], and

$$F = x_r - \hat{x} = x_r - \alpha \sin \phi\tag{2}$$

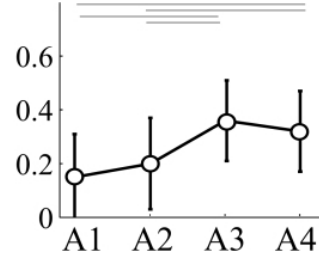
is the error signal driving learning, i.e. the difference between the input signal and its estimate $\hat{x}$. The insert in the lower right corner of Fig.1 captures a typical learning behavior of an AO when the input frequency is abruptly changing at a certain time (gray dotted line).

III. LOCOMOTION ASSISTANCE

In its simplest form (1), an AO can thus be viewed as a state observer, estimating the features of a rhythmic input signal. If this signal is produced by a human user during locomotion — such as the hip angular pattern during walking — the AO could be used for instance to deliver a phase-dependent assistive torque to an exoskeleton [8] or even to a prosthesis replacing another missing joint [9]. Similarly, the same system could be used to predict the signal in the near future, via a time-shifted version of the estimator, i.e. $\hat{x}(t + \delta t) = \alpha \sin(\phi + \omega \delta t)$. This is the approach we followed in [10] in order to provide positive power assistance by attracting the user’s hips to their own predicted future trajectory through a compliant force field. In the same paper, we reported how AO could be used to provide torque assistance based on a dynamic model of the task and estimates of kinematic derivatives [5].



(a) Methods, adapted from [6].



(b) Results, adapted from [7].

Fig. 2. Smoothing assistance framework. (a) When requested to produce an upper-limb movement (here, continuous drawing of a circle), a stroke patient typically produces a jerky trajectory (here p_{pat}). The AO (1) continuously learns a smoother version of this movement p_{osc} . An assistive force proportional to their difference $F_{smoothness}$ is delivered in order to produce smoother movements. (b) Evolution over 4 assessment days (pre-treatment: A1, A2 — post-treatment: A3 and A4) of 13 stroke patients during the execution of a typical rhythmic task in a metric capturing movement harmonicity. The error bars represent the 95% confidence intervals. The horizontal lines capture the assessment numbers being significantly different from each other.

IV. “SMOOTHING” ASSISTANCE

More recently, we tested AOs to provide specific assistance to patients with motor disorders, in particular regarding the execution of upper-limb rhythmic tasks. Indeed, stroke patients typically produce jerky reaching movements, and this has been observed in rhythmic tasks as well [11]. In [6], we developed an assist-as-needed control framework for stroke patients performing rhythmic movements. More precisely, an upper-limb assistive robot delivered a force that was directly proportional to the AO error signal F (2), see Fig.2(a). Therefore, if the patient was producing a perfectly harmonic movement — what we considered to be “perfectly smooth” in that work — F converged to 0 and no assistance was provided; while the assistive field would encourage the movement to be smoother otherwise. Importantly, since the AO was continuously learning from the user’s input signal, such assistance was providing no energy to the user on average, therefore encouraging active participation.

We conducted a longitudinal study with 13 post-stroke patients who received this robotic-based therapy during 12 sessions of 18-min spread over 1 month [7]. Their performance was assessed twice before the therapy (A1 and A2), once just after (A3) and once three months after the last session of the therapy, to assess the long-term retention of the intervention (A4). Fig.2(b) reports one of the main results of this study, namely the level of harmonicity of a typical self-produced rhythmic movement (i.e. while receiving no more assistance from the robot). In short, this index is bounded between 0 and 1, 1 corresponding to a pure harmonic movement. This figure shows that the therapy improved the patients’ capacity to produce autonomous rhythmic movement with a better harmonicity, even months after the intervention ended. More intriguingly, we also reported some improvements in performing discrete movements, likely recruiting some transfer mechanisms which still have to be unveiled.

V. CONCLUSION

In this document, we overviewed our recent efforts in using adaptive oscillators for modeling and assisting rhythmic movements, both with the upper- and the lower-limb. We state that this mathematical tool is particularly suited to be

used as a template for closed-loop interactions between a (disabled) user and an assistive robot. Since both parties continuously adapt to each other, the robotic assistance is suited to the current user’s needs, while promoting his/her active participation to the task.

In future work, we will adapt the smoothing framework reported in Section IV to the lower-limb, and test it with patients having specific gait disorders while using a wearable device. We will further continue our efforts in combining these AOs with task-specific assistive strategies, in order to support the user not only in level-ground walking but also in more energetically challenging tasks.

REFERENCES

- [1] N. Hogan and D. Sternad, “Dynamic primitives of motor behavior,” *Biol Cybern*, vol. 106, pp. 727–739, 2012.
- [2] K. Minassian, U. S. Hofstoetter, F. Dzeladini, P. A. Guertin, and A. Ijspeert, “The human central pattern generator for locomotion: Does it exist and contribute to walking?” *The Neuroscientist*, vol. 23, pp. 649–663, 2017.
- [3] N. Van der Noot, A. J. Ijspeert, and R. Ronsse, “Bio-inspired controller achieving forward speed modulation with a 3d bipedal walker,” *The International Journal of Robotics Research*, vol. 37, pp. 168–196, 2018.
- [4] L. Righetti, J. Buchli, and A. J. Ijspeert, “Dynamic hebbian learning in adaptive frequency oscillators,” *Physica D*, vol. 216, pp. 269–281, 2006.
- [5] R. Ronsse *et al.*, “Real-time estimate of velocity and acceleration of quasi-periodic signals using adaptive oscillators,” *Robotics, IEEE Transactions on*, vol. 29, pp. 783–791, 2013.
- [6] P. Leconte and R. Ronsse, “Performance-based robotic assistance during rhythmic arm exercises,” *Journal of neuroengineering and rehabilitation*, vol. 13, 2016.
- [7] P. Leconte, G. Stoquart, T. Lejeune, and R. Ronsse, “Rhythmic robotic training enhances motor skills of both rhythmic and discrete upper-limb movements after stroke: a longitudinal pilot study,” *Int J Rehabil Res*, vol. 42, pp. 46–55, 2019.
- [8] V. Ruiz Garate *et al.*, “Experimental validation of motor primitive-based control for leg exoskeletons during continuous multi-locomotion tasks,” *Frontiers in Neurobotics*, vol. 11, 2017.
- [9] S. Heins *et al.*, “Compliant control of a transfemoral prosthesis by combining feed-forward and feedback,” in *Biomedical Robotics and Biomechatronics (BioRob)*, 2020 8th IEEE RAS and EMBS International Conference on, to be published.
- [10] R. Ronsse *et al.*, “Oscillator-based assistance of cyclical movements: model-based and model-free approaches,” *Med Biol Eng Comput*, vol. 49, pp. 1173–1185, 2011.
- [11] M. Simkins, A. Burleigh Jacobs, and J. Rosen, “Rhythmic affects on stroke-induced joint synergies across a range of speeds,” *Exp Brain Res*, vol. 229, pp. 517–524, 2013.