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Real-time smoothness-based assistance during rhythmic arm movements

Patricia Leconte¹,³ and Renaud Ronsse¹,²,³

Abstract—Rhythmic and discrete movements are two fundamental motor primitives being - at least partially - controlled by different neural pathways. After a stroke, both primitives can be impaired. However, current upper-limb therapies - both conventional and robot-assisted - train mainly discrete functional movements. In order to recover the complete motor repertoire, training both movements should be offered with dedicated exercises. The paper elaborates a new performance-based robotic assistance to train rhythmic movements with a rehabilitation robot. More precisely, it develops and validates a performance-based smoothness assistance. The developed assistance aims at smoothing the movement being performed, based on a real-time estimate of the movement smoothness.

I. INTRODUCTION

Rhythmic and discrete movements recently emerged as two of the most fundamental units of the upper- and lower-limb human motor repertoire. Rhythmic movements capture periodic movements like hammering or scratching, while discrete movements capture movements between a succession of postures with zero velocity and acceleration, like reaching and pointing [3], [4]. These two fundamental motor primitives are controlled by distinct neural circuitries, at least partially [3], [5], [6], [7], [8], [9], [10].

After a stroke, both rhythmic and discrete movements can be impaired [11], [12], [13], [14]. Recently, we compared the performance in executing both movements in the same stroke population. As a main conclusion, we found that rhythmic arm movements are less affected than discrete ones, although both displayed impairments compared to healthy subjects [15]. In particular, stroke patients decelerated more than healthy subjects at the movement reversal, and some patients displayed a larger amount of submovements.

Most post-stroke upper-limb therapies tend to focus on functional and thus mainly discrete movements [16]. If rhythmic and discrete movements are two distinct primitives, they deserve specific and differentiated training to permit the full recovery of the complete motor repertoire. This is a necessary condition to recover autonomy in daily-life activities requiring a combination of rhythmic and discrete movements (such as wiping a table or playing the piano [5]). Furthermore, because our recent findings also revealed smaller affection of rhythmic movements after stroke [15], a progression in the exercises could also be proposed. Discrete elements could be combined with rhythmic movements, supporting the execution of movements with a higher degree of impairment by those that are performed more stably. This calls for the development of post-stroke therapies tailored for rhythmic movement training, which is the main contribution of the present study.

Robotic devices are particularly suited for implementing such therapies, with a specific focus on movement intensity. Rehabilitation robots enable patients to practice well-specified motor actions and can deliver an appropriate amount of assistance to assist patients in improving their motor behavior [17], [18]. Motor performance can be computed in real-time by the robot controller, allowing for continuous adaptation of the type and amount of assistance. The patient only receives the necessary support and is prevented from slacking [18]. This assistance principle is also called "assistance as needed" and has progressively emerged as a hallmark of successful robot-assisted therapies [17], [18].

Several upper-limb robot-assisted therapies implement the assist-as-needed principle for discrete movements through different strategies. One type of strategy delivers assistance proportional to the trajectory error with respect to a predefined trajectory [19], [20], [21]. Another assistance approach relies on dynamical systems and adapts the assistance parameters as a function of the patient performance [22]. Other contributions tune the amount of assistance across sessions as a function of the performance during the preceding session [23]. Another method [20] performs an online adaptation of the amount of support depending on the activity (for a survey, see [17]).

In contrast to these approaches, a rhythmic movement therapy should exploit the cyclic nature of the movement to anticipate the future trajectory based on previous cycles. This can be achieved by using adaptive oscillators [24]. These mathematical tools are particularly suited to track the main features of a typical rhythmic movement (like amplitude and frequency). This continuous assessment allows the robot to constantly seek to improve movement features with the appropriate amount and type of assistance. Moreover, this approach naturally implements trajectory-free assistance algorithms.

Our previous work already paved the way in using adaptive oscillators to deliver trajectory-free assistance for upper- [25] and lower-limb [26] rhythmic movements. These contributions focused on movement assistance for healthy subjects, showing evidence of decreases in metabolic consumption when the assistance was switched on. The present study is the first to describe a metric-based assistance method for patients with motor disorders, with emphasis on the potential to assist

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rhythmic movements as a function of the patient needs. In particular, we will focus on a specific landmark, namely the movement smoothness [13], [14], [29]. Indeed, movement smoothness is known to be impacted by stroke and can be improved through rehabilitation therapy.

This paper outlines the performance-based assistance method in details. The method was validated with data from simulations and two stroke patients with upper-limb impairments. The reported results show that our performance-based smoothness assistance method can (i) enhance motor-performance, (ii) give appropriate assistance according to patient performance, and (iii) maintain active patient participation in the task so that no slacking effect is reported.

II. METHODS

The main interest of our method is that it can assist the smoothness feature of the movement only if needed, without having to impose a predefined trajectory to the patient. Therefore, the method requires measuring (Fig. 1-1) and quantifying (Fig. 1-2) the smoothness feature of patient movement in real-time. The method must also compute and deliver the appropriate amount of assistance as a function of the performance (Fig. 1-3).

![Fig. 1. Outline of the overall control strategy of the performance-based assistance. First, the movement features are computed by the adaptive oscillator (1) and serve as input to compute the real-time performance in smoothness (2). This feature is then used to compute the gains to tune the level of the assistance force (3).](image)

The most comprehensible way to develop the proposed assistance method requires focusing on a simple rhythmic movement. This "ideal" movement is a rhythmic circular trajectory executed with the upper-limb. The parameters shaping this movement are the amplitude, offset (the position of the circle center), and the rotational frequency. The desired movement kinematics are characterized by the vectorial position in Cartesian space as a function of time:

\[
p_d = \begin{pmatrix} x_d \\ y_d \end{pmatrix} = \begin{pmatrix} \phi_{x,d} + \alpha_d \sin \omega_d t \\ \phi_{y,d} - \alpha_d \cos \omega_d t \end{pmatrix}
\]

where \( \alpha_d \) is the desired amplitude of movement, \( \omega_d \) is the angular frequency and \( \phi_{x,d} \) and \( \phi_{y,d} \) are the desired offsets along the x- and y-axes, respectively.

Real-time measurement of the movement features

Adaptive oscillators are particularly suited for estimating the real-time state variables of a rhythmic movement [24], [27], [28]. From the ideal movement in (1), an adaptive oscillator can learn an equivalent movement captured by the following model:

\[
p_{osc} = \begin{pmatrix} x_{osc} \\ y_{osc} \end{pmatrix} = \begin{pmatrix} \phi_{osc,x} + \alpha_{osc} \sin \phi_{osc} \\ \phi_{osc,y} - \alpha_{osc} \cos \phi_{osc} \end{pmatrix}
\]

where \( \alpha_{osc} \) is the learned amplitude, \( \phi_{osc} \) is the learned phase (the time integral of the learned frequency \( \omega_{osc} \)), and \( \phi_{osc,x} \) and \( \phi_{osc,y} \) are the learned offsets. These variables obey learning dynamics being governed by:

\[
\dot{\phi}_{osc} = \omega_{osc} + v_p \left( F_x \cos \phi_{osc} + F_y \sin \phi_{osc} \over \alpha_{osc} \right), \quad (3)
\]

\[
\dot{\omega}_{osc} = v_p \left( F_x \cos \phi_{osc} + F_y \sin \phi_{osc} \over \alpha_{osc} \right), \quad (4)
\]

\[
\dot{\alpha}_{osc} = \eta \left( F_x \sin \phi_{osc} - F_y \cos \phi_{osc} \right), \quad (5)
\]

\[
\phi_{osc,x} = \eta F_x, \quad \phi_{osc,y} = \eta F_y, \quad (6)
\]

where \( F_x = x - x_{osc} \) and \( F_y = y - y_{osc} \) are the error signals that capture the difference between the oscillator input (x and y, the 2D hand position measured by the device in this case) and the estimated position output.

By properly tuning the learning gains \( \nu_p, \nu_p, \) and \( \eta, \) the output signal will synchronize with the input signal after only a few cycles while learning the actual input features in the internal state variables [27]. If the input signal contains higher harmonics in its frequency spectrum, the oscillator output can be considered as a "smoothed" or filtered version of the input, although both will be phase-synched on average. In sum, this adaptive oscillator provides real-time estimates of the parameters of a time-varying periodic signal while filtering this signal in its output.

Interestingly, this can also provide a smooth estimate of the signal derivatives. For instance, the estimate of the signal’s first derivative is obtained by the time-differentiation of (2):

\[
p_{osc} = \begin{pmatrix} \dot{x}_{osc} \\ \dot{y}_{osc} \end{pmatrix} = \begin{pmatrix} \alpha_{osc} \omega_{osc} \cos \phi_{osc} \\ \alpha_{osc} \omega_{osc} \sin \phi_{osc} \end{pmatrix}
\]

More details about the mathematical foundations of the adaptive oscillator can be found e.g. in [24].

Real-time smoothness performance computation

Assessing the smoothness of a discrete movement after completion (off-line) has recently been the focus of many studies (see e.g. [13], [14], [29]). The challenge lies in determining a dimensionless metric that is independent of the movement amplitude and duration while having a monotonic response to the motion characteristics. The smoothness has to decrease when the amount of submovements and the inter-submovement duration decrease [29]. Several metrics were suggested and analyzed, such as the normalized mean absolute jerk, the number of peaks in the velocity profile, the logarithmic dimensionless jerk, the spectral arc length, and the speed arc length [13], [14], [29].

In our approach, the real-time measurement of movement smoothness is required to continuously adapt the assistance. The previous metrics mentioned are thus ineligible since they can only provide an off-line smoothness estimate after the completion of several movement cycles. Hence, we propose measuring the smoothness performance in real-time by comparing the actual velocity of the patient with the
desired velocity computed by the adaptive oscillator (8); i.e., the filtered version of the patient actual velocity. This error is normalized with respect to the angular velocity (the product of \(\omega_{osc}\) and \(\alpha_{osc}\)) to obtain a dimensionless metric:

\[
\eta = \frac{\sqrt{(\dot{x}_{osc} - \dot{x})^2 + (\dot{y}_{osc} - \dot{y})^2}}{\omega_{osc} \alpha_{osc}} \tag{9}
\]

Next, we compute the numerical differentiation of this velocity error signal and normalize it again with the angular damping coefficient. To render the behavior of a spring with mass of the robot. In (12), \(p\) and \(\dot{p}\) denote the measured positions and velocity of the patient hand, respectively.

To prevent the patients from slacking [18], the level of assistance has to evolve as a function of the real-time performance. If the smoothness error is high, the gain of the smoothness assistance has to increase. If the performance improves, the gain should decrease in order to encourage the patient to stay active. A low-pass filter is thus used to tune the gain of the assistance force \(k_{sm}\), see Fig. 3. The gain evolves dynamically between 0 (no assistance if the performance is good) and a maximum value \(k_{max,sm}\) (if the performance is poor) through a scaling factor \(k_{%sm} \in [0,1]\), such that \(k_{sm} = k_{%sm} k_{max,sm}\). The input of the filter is the performance index \(\varepsilon_{sm}\) (11). \(\varepsilon_{min,sm}\) is the minimum error tolerated before \(k_{%sm}\) increases, and \(\varepsilon_{max,sm}\) is the maximal error causing \(k_{%sm}\) to saturate to 1. The time constant of this filter is set to \(\tau_g\) seconds.

\[
\varepsilon_{sm} = a \omega_{osc} (|\xi| - \varepsilon_{sm}) \tag{11}
\]

where \(a\) is a constant gain tuning the frequency-dependent time constant of the filter. If the movement is performed as an ideal circle of constant tangential velocity, \(\eta\), \(\xi\), and thus \(\varepsilon_{sm}\) will converge towards 0. Moreover, a circular movement performed with a constant acceleration will cause \(\varepsilon_{sm}\) to converge towards 0 since the velocity error \(\eta\) will reach a plateau. The more fluctuations there are in the difference between the patient velocity and the ideal sinusoidal velocity captured by the adaptive oscillator, the higher \(\varepsilon_{sm}\) will be.

**Assistance force**

Having an estimate of the smoothness performance offers to deliver a smoothness assistance if the performed movements are detected to be jerky, i.e. to deviate too much from the ideal movement given by (1) (Fig. 1-3).

Smoothness assistance is provided by a virtual damped spring between the current estimated position provided by the adaptive oscillator and the actual patient position (Fig. 2). This type of assistance guides the patient hand to a "smoothed version" of its own movement since the adaptive oscillator continuously synchronizes to its input - i.e. the movement being performed - while filtering out the frequency content out of its main harmonic. The oscillator neither lags behind nor leads the patient hand on average since it is phase-synched to it. Accordingly, the force applied to the patient hand (\(F_{smoothness}\)) is equal to:

\[
F_{smoothness} = k_{sm}(p_{osc} - p) + c(\dot{p}_{osc} - \dot{p}). \tag{12}
\]

where \(k_{sm}\) is the adaptive stiffness of the spring and \(c\) is the damping coefficient. To render the behavior of a spring with critical damping, \(c = 2\sqrt{mk_{sm}}\) (\(m\) is the equivalent virtual mass of the robot). In (12), \(p\) and \(\dot{p}\) denote the measured positions and velocity of the patient hand, respectively.

**Validation with simulated data**

Before validating the performance-based assistance with patient data, it was tested with simulated jerky circular movements. These unideal rhythmic signals were generated by augmenting a smooth rhythmic circular movement (similar to (1)) with lateral and longitudinal errors of time-varying amplitude and frequency, captured by:

\[
\alpha_{jerky} = \alpha(1 + \delta_{lat}\sin(\omega_{lat}t)), \tag{13}
\]

\[
\omega_{jerky} = \dot{\alpha}(1 + \delta_{long}\cos(\omega_{long}t)), \tag{14}
\]

\[
\phi_{jerky} = \int \omega_{jerky} dt \tag{15}
\]

where \(\alpha\) and \(\dot{\alpha}\) are the mean amplitude and frequency of the simulated jerky movement, while \(\omega_{lat}\) and \(\omega_{long}\) capture the frequency of the lateral and longitudinal errors, and \(\delta_{lat}\) and \(\delta_{long}\) capture the amplitude of the lateral and longitudinal errors, respectively. Longitudinal error mostly impacts the
signal temporality, while lateral errors mostly impact the signal spatial distribution.

These simulated jerky signals were first used to validate the convergence of the adaptive oscillator towards the average amplitude $\bar{\alpha}$ and frequency $\bar{\omega}$. The values of the parameters that were used are shown in Table 1 ("Sim. data" column). $\bar{\alpha}$ was set to 5cm and $\bar{\omega}$ was set to 3.14rad/s. This test was performed both with longitudinal ($\delta_{\text{long}} = 0.6$ and $\omega_{\text{long}} = 4\bar{\omega}$) and lateral errors ($\delta_{\text{lat}} = 0.2$ and $\omega_{\text{lat}} = 4\bar{\omega}$).

Next, to validate the performance-based assistance, we built a signal composed of different types of errors. This signal was composed of (i) five cycles of unperturbed circular rhythmic movement ($\bar{\alpha} = 5$cm and $\bar{\omega} = 3.14$rad/s, $\delta_{\text{lat}} = 0$ and $\delta_{\text{long}} = 0$), followed by (ii) five cycles of jerky movements with lateral errors ($\delta_{\text{lat}} = 0.2$, $\omega_{\text{lat}} = 4\bar{\omega}$, $\bar{\alpha} = 5$cm, $\bar{\omega} = 3.14$), and (iii) five cycles of jerky movements with longitudinal errors ($\delta_{\text{long}} = 0.6$, $\omega_{\text{long}} = 4\bar{\omega}$, $\bar{\alpha} = 5$cm and $\bar{\omega} = 3.14$rad/s). These simulated pathological movements were separated from each other by another five periods of unperturbed rhythmic circular movements.

The signal was used to compute the real-time smoothness metric and the performance-based assistance. The values of the parameters used to compute the metrics and gains are again displayed in Table 1 ("Sim. data" column). $\bar{\omega}_{\text{long}}$ was this time tuned to obtain a learning time constant equal to 3s.

### TABLE I

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Sim. data</th>
<th>Pat. data</th>
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<tbody>
<tr>
<td>$\alpha$</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>$\omega_0$</td>
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<td>2.2</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.67</td>
<td>0.2</td>
</tr>
<tr>
<td>$\tau$</td>
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<td>1</td>
</tr>
<tr>
<td>$\varepsilon_{\text{min},\text{sm}}$</td>
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<td>0.0025</td>
</tr>
<tr>
<td>$\varepsilon_{\text{max},\text{sm}}$</td>
<td>0.009</td>
<td>0.009</td>
</tr>
</tbody>
</table>

**Validation with experimental data**

Finally, the performance-based assistance was implemented on an end-effector robot, and the protocol was tested with two stroke patients (see Table 2). Both patients gave written informed consent to participate to the study, which was approved by the ethical committees of the Université catholique de Louvain.

### TABLE II

<table>
<thead>
<tr>
<th>Age</th>
<th>Gender</th>
<th>Time post-stroke</th>
<th>FMA</th>
<th>Hemiplegic side</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>61</td>
<td>Male</td>
<td>4y</td>
<td>23</td>
</tr>
<tr>
<td>P2</td>
<td>50</td>
<td>Male</td>
<td>1y</td>
<td>24</td>
</tr>
</tbody>
</table>

**Experimental apparatus**: The robotic assistance was implemented on an upper-limb end-effector robot, REAplan, which was developed within our university. The robot is composed of (i) a height-adjustable horizontal table, (ii) a handle equipped with force sensors held by the participant, (iii) two motors actuating the handle in the horizontal plane, (iv) a flat screen and loudspeakers in front of the participant, which can provide visual feedback of the position of the handle and any other visual or auditory information, and (v) an interface next to the robot for the therapist. All these components are shown in Fig. 4.

![Planar end-effector robot (REAplan) used to validate the performance-based assistance. The patient is seated in front of the device and holds the handle with his/her hand.](image)

**Therapy**: Patients were asked to perform rhythmic circular movements while receiving smoothness assistance during half of the trials. They were further asked to stay inside a circular path being 4cm wide.

Patients performed 10 trials which each lasted 40 seconds. They received assistance during half of these trials with random distribution. In the trials with assistance, the adaptive oscillator gains were this time tuned to obtain a learning time constant equal to 10s (see "Pat. data" column in Table 1) [27]. Patients received at least one minute of rest between two consecutive trials.

To validate our approach, we show that the assistance (i) adapts to the real-time motor performance, (ii) enhances the global motor performance, and (iii) does not increase with time (no slacking).

**III. RESULTS AND DISCUSSION**

**Validation with simulated data**

**Adaptive oscillators**: Simulation data confirm the capacity of the adaptive oscillator to quickly synchronize to an input rhythmic movement while learning its features in state variables. Fig. 5 (left) shows an illustration of the adaptive oscillator synchronizing with the simulated data with a mean amplitude of $\bar{\alpha} = 5$cm and mean angular velocity of $\bar{\omega} = 3.14$rad/s. The state-variables are also displayed and reach steady-state after about two periods (3 seconds), which corresponds to the expected settling time (see Table 1 and [27]). The oscillator output produces a smooth quasi-sinusoidal version of the distorted input and is fully synchronized after the same amount of time.
This result confirms that the state-variables $\omega_{osc}$ and $\alpha_{osc}$ are good candidates for estimating the real-time frequency and amplitude of quasi-harmonic movements performed by the patients. They can also be extracted in real-time during the therapy given the low computational cost of the discrete-time integration of the oscillator state equations.

Performance-based assistance: Fig. 6 shows the evolution of the gains as a function of the smoothness error (bottom panel). From top to bottom, the different panels show (i) the position signals, (ii) velocity signals, (iii) absolute error in velocity $\eta$, its time derivative $\xi$, and the smoothness metric $\epsilon_{sm}$ (the filtered version of $\xi$). The assistance gain responds as expected. When the error of the corresponding assistance is above $\epsilon_{min}$, the assistance increases. If the error is above $\epsilon_{max}$, the gain saturates to 1 with a settling time of about 1 second.

Validation with patients

Fig. 5 (right) shows the behaviour of the adaptive oscillator when adapting to a real patient 2D trajectory ($x$ and $y$ coordinates). The performance is thus very similar as with the simulated data.

Performance-based assistance adapts to the real-time motor performance: Fig. 7 illustrates the evolution of the error signals during a trial without assistance (upper panels) and with assistance (bottom panels). The left bottom panel also shows the evolution of the level of smoothness assistance.
When the error increases, the assistance increases accordingly.

**Performance-based assistance enhances motor performance:** On the right side of Fig. 7, the hand trajectory during a trial with and without assistance is traced. This clearly shows that the hand trajectory was smoother when assistance was provided. This observation can be quantified by measuring the mean smoothness errors during the trials with and without assistance (Fig. 8-C). As expected, the error was significantly higher during the trials without assistance than with assistance for both patients (one-way anova, assistance effect: patient 1, $F_{(1,8)} = 9.89, p = 0.01$; patient 2, $F_{(1,8)} = 5.96, p = 0.04$).

This result shows that the smoothness assistance had the expected impact on motor performances, by improving the smoothness feature of both patients movements.

**Performance-based assistance does not lead the patient to slack:** The slacking hypothesis suggests that when receiving too much assistance, a patient relies on the assistance and stops providing the maximum effort to execute the task alone [18]. This can be observed both within a trial and across trials. If patients display slacking behavior, the amount of assistance should increase over time. The evolution of the smoothness assistance gain is displayed in figures 8-A (inter trials) and B (between trials) for both patients. Fig. 8-A shows the amount of assistance provided during the five assisted trials for both patients (colored dashed lines) and their average (black solid line). The figure clearly illustrates that the assistance did not increase over time during the trials, except during the initialization phase where the level of assistance reached steady-state. Fig. 8-B shows the mean assistance provided during each trial and confirms that the assistance was also not increasing across the 5 trials. These results show that the patients stayed equally active during the successive trials. Indeed, if they would have displayed a slacking behavior, the movement would have been degraded and the assistance gains would have increased accordingly.

**IV. Conclusion**

Rhythmic and discrete movements are considered to be two different motor primitives, and both are affected after stroke. Therefore, both movements should be trained during post-stroke therapies. Currently, mainly functional discrete movements are recruited during post-stroke therapies, and similarly, the majority of assistance methods being developed for rehabilitation robots target only discrete movement training. To bridge this gap, our study presented a new performance-based robotic assistance training for rhythmic movements. It should ideally complement similar discrete-specific therapies in order to recover the most complete motor repertoire.

The developed assistance method relies on the repetitive nature of rhythmic movements to assist the patient without constraining the participant to follow a predefined trajectory. The assistance force is modulated as a function of a real-time smoothness metric and therefore assist the patient as needed to prevent slacking. Our approach ideally combines several blocks: an adaptive oscillator that extracts the movement state variables while isolating the movement’s main harmonic, an estimator that compute the real-time movement smoothness, and an adaptive block that compute the smoothness assistance force. Notably, these blocks consist of a few dynamic equations and can thus be implemented in a discrete-time version with a limited amount of code and reasonable computational cost. Moreover, the presented performance-based assistance could be extended to more functional rhythmic movements such as wiping a table, brushing teeth or even walking [26]. This would however require to augment the adaptive oscillator with the capacity to learn more harmonics of the input signal [27], and to transfer our assistive approach to more complex devices like exoskeletons.

These different blocks were tested using both simulated and actual experimental data. The simulation data mainly served to validate the computing of the smoothness metric and the corresponding assistance gain using signals with controlled distortions. Patient data revealed the method efficiency in assisting patients to produce smoother movements while keeping them active in the task.

**References**
