Adaptive Position Anticipation in a Support Robot for Overground Gait Training Enhances Transparency

Christophe Everarts, Heike Vallery, Marc Bolliger and Renaud Ronsse

Abstract— **Rehabilitation robots being developed nowadays rely on force and/or impedance control. This is guided by clinical evidence showing better performance if the patient is left with the capacity to influence the robot trajectory. The simplest, yet fundamental, mode of force control is when the robot has to be transparent, i.e. to apply no forces/torques on the patient. This mode is useful both in scenarios where the robot has to apply pinpointed support during some training phases and be transparent otherwise, and for any force controller in general, to avoid the reference forces to be polluted by the robot own dynamics. This contribution proposes a method to improve transparency on a support robot for overground training. The method consists in learning the patient's movement by using adaptive oscillators and then anticipate its future evolution in order to synchronize the robot movement. In experiments with human subjects walking in the gait support robot FLOAT, this method can decrease the undesired oscillations of the support force applied to the human user by up to 50 %.**

I. INTRODUCTION

In rehabilitation after neurological injury, robots are becoming more and more popular tools to improve the therapy efficiency. Consequently, diverse robots have been developed, both for the upper [1]–[5] and lower extremities [6]–[10].

Robots being used with patients allow to let them perform several kinds of functional movements, with a high degree of accuracy and repeatability. The use of robotic devices is less tiresome for the therapist than a classical therapy. Moreover, robotic devices can perform quantitative and objective measurements and assist the patient through different and innovative control strategies. Several clinical studies tend to show that robots can improve recovery after stroke [11]–[15].

In impedance and force controllers, a fundamental requirement is transparency: The robot's intrinsic dynamics should not lead to undesired interaction forces on the human. A particular challenge is to mask a robot's inertia [16]–[18].

CE and RR were supported by the European Community's 7th Framework Programme (FP7/2007-2013) under Grant 287894 (CYBERLEGs); and the F.R.S.-FNRS (1.5025.12 and 2012/V 3/5/394 - IB/JN - 14808).

HV and MB were supported by Walter L. & Johanna Wolf-Foundation.

Ch. Everarts and R. Ronsse are with the Center for Research in Mechatronics, Institute of Mechanics, Materials and Civil Engineering, Université catholique de Louvain, B-1348 Louvain-la-Neuve, Belgium. {christophe.everarts,renaud.ronsse}@uclouvain.be

H. Vallery is with the Department of BioMechanical Engineering, Delft University of Technology, 2628 CD Delft, The Netherlands; the Sensory-Motor Systems (SMS) Lab, ETH Zurich, 8092 Zurich, Switzerland; and the Department of Biomedical Engineering, Khalifa University of Science, Technology and Research, Abu Dhabi, UAE. h.vallery@tudelft.nl

M. Bolliger is with the Spinal Cord Injury Center, Balgrist University Hospital, University of Zurich, 8092 Zurich, Switzerland. mbolliger@paralab.balgrist.ch

This contribution presents a new method to improve transparency, based on the use of adaptive oscillators [19]–[25]. An adaptive oscillator is a set of differential equations which can synchronize to a periodic signal by learning this signal's features (i.e. frequency, amplitudes, phases) within its state variables. As such, an adaptive oscillator not only achieves adaptive synchronization to the input signal, but also performs a kind of real-time Fourier decomposition of this input through a sum of different harmonic signals.

Practically, this method was put to test on a real robot, namely the "FLOAT" being developed within the Spinal Cord Injury Center at the Balgrist Hospital in Zurich [26], [27]. This cable-based robot provides overground support for gait rehabilitation in a large workspace. Transparency is particularly relevant in this kind of robot, since we might want to provide postural assistance only when a fall is detected, or to provide a constant supporting force in the vertical direction, while "hiding" the natural oscillations created by the robot own dynamics, both in the vertical and horizontal directions. As an initial investigation, this paper focuses only on the vertical direction, i.e. with the objective to reduce the undesired oscillations along the z axis.

This paper is organised as follows. In Section II, we briefly describe the FLOAT robot used to test the predictive method. We describe the mechanical design and the controller principle. In Section III, we introduce the concept of adaptive oscillators and their implementation in the robot controller. In particular, we propose a new method to achieve robust frequency learning despite the intrinsic variability of the signal during natural walking. In Section IV, we present methods to compare the previous and the new controller, only in the vertical direction and with healthy subjects. In Section V, we present preliminary results with the previous and the new controller. We clearly establish that the predictive controller reduces the force oscillation around the expected constant supportive force by up to 50 %. In Section VI, we discuss the perspective of extending the adaptive oscillators to improve transparency also in the horizontal directions (both forward and lateral), pending an appropriate coordinate change and a velocity learning algorithm. Finally, Section VII concludes the paper.

II. ROBOT CONCEPT

The FLOAT robot used to implement the prediction method proposed in this paper has been developed by Vallery et al. [27]. This robot is illustrated in Figure 1.

This robot can provide a vectorial (3D) force to support a human during walking. This force is applied through four

978-1-4673-6024-1/13/$31.00 ©2013 IEEE

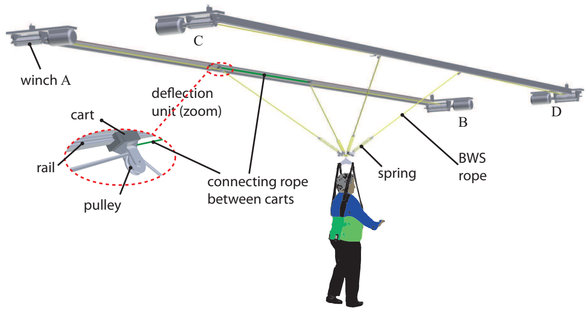

Fig. 1. FLOAT concept. More details can be found in [27].

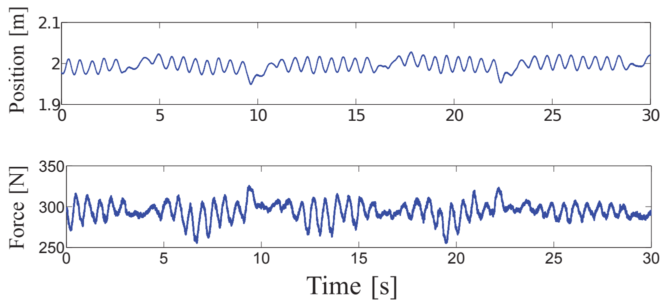

Fig. 2. Vertical position and force of the node during a representative walking task (30 seconds, corresponding to about 5 crossings of the robot workspace). The desired assistive force was set to 30kg, such that the expected measured vertical force should be constant and around 300N.

cables connected to a single node, being in turn connected to the human via a beam and a harness, such that no moments are transmitted, only forces.

Cables are tensed by four winches which are the four controllable degrees of freedom. These cables are connected from the node to the winches through pulleys which are mounted on four carts. Each pair of carts are connected by a cable to form one trolley, both running independently on two parallel rails.

The cables are further connected to the node through springs which are used to measure the force in each cable with potentiometers. The node force is estimated from these measurements by using a geometric model. Laser sensors measure the position of each trolley and each winch has an absolute encoder to measure the cable length. More details on the robot design can be found in a companion paper, accepted for publication to the same conference [27].

The robot controls force on the node in Cartesian space by means of a proportional-integral force controller. Mapping from the resulting three Cartesian force components to the four winch torques is not unique and therefore allows for additional control action to influence trolley dynamics: An asymptotically stable relative movement of the trolleys is enforced, such that the four pulleys form the corners of a rectangle above the subject.

In the current implementation, force control performance in vertical direction needs to be improved, because there can be peak undesired interaction forces of up to 40 N acting on the subject (Figure 2, bottom). As these undesired forces occur in response to human movement, which is almost periodic in Z direction (Figure 2, top), the use of an oscillator concept seems promising [19], [20].

III. Estimator : Adaptive oscillator

In order to improve transparency, we anticipate movement of the node (caused by movement of the subject), and we let the winches facilitate this movement, by adding predictive terms to the existing force controller. Since the signals being considered in this paper are quasi-periodic, we use adaptive oscillators [19], [20] to perform this anticipation.

A. Integration in the existing controller

The method proposed here to increase the robot transparency requires to add predictive components to the existing PI force controller. The calculation of these predictive terms is separated into three different layers.

a) The predictive layer: predicts the future position of the node with an estimator (i.e. an adaptive oscillator).

b) The equilibrium layer: calculates the winch positions required to apply the reference force on the node, considering a static equilibrium for a given position (i.e. no dynamic effect taken into account).

c) The position control layer: is a proportional-gain position controller giving reference forces to reach the winch positions calculated in the second layer.

Without the prediction layer, the equilibrium layer would calculate the winch position needed to reach static equilibrium with respect to the current node position and reference node force. Due to computational delays, the mechanical response of the robot, and the controller limited bandwidth, the control signal sent to the motors would thus be delayed compared to the actual node position.

Therefore, the idea developed in this paper is to feed this layer with an estimation of the future node position, in order to compute the winch position to reach static equilibrium a few milliseconds forward in time. If this time anticipation corresponds to the accumulated delay, better transparency should be observed since the controller should bring the winches and trolleys to their static equilibrium positions with more accuracy.

B. Principle of an adaptive oscillator

An adaptive oscillator is used as an efficient estimator of the node future position. More precisely, it is a dynamical system having the capacity to synchronize to a quasi-periodic input by learning its features in state variables. The adaptive oscillator used in this paper is similar to the one presented in [21] and achieves the learning of a quasi-periodic signal $\theta(t)$ in an estimator $\hat{\theta}(t)$. This estimator performs a kind of real-time Fourier decomposition of the input signal, keeping K harmonics (Figure 3):

$$\hat{\theta}(t) = \sum_{i=0}^{K} \alpha_i \sin(\phi_i) = \sum_{i=0}^{K} \alpha_i \sin(i\omega t + \varphi_i) \qquad (1)$$

where ϕ_i, $i\omega$ and α_i are the phase, frequency and amplitude of the harmonics. Those parameters are the state variables of the dynamical system actually representing the adaptive oscillator:

$$
\begin{aligned}
\dot{\phi}_i(t) &= i\omega(t) + \nu_\phi \frac{F(t)}{\sum_i \alpha_i(t)} \cos\phi_i(t) \\
\dot{\omega}(t) &= \nu_\omega \frac{F(t)}{\sum_i \alpha_i(t)} \cos\phi_1(t) \\
\dot{\alpha}_i(t) &= \eta F(t) \sin\phi_i(t)
\end{aligned}
\tag{2}
$$

where ν_ϕ, ν_ω and η are the learning gains determining respectively the speed of phase, frequency and amplitude synchronization to the error signal $F(t) = \theta(t) - \hat{\theta}(t)$. Note that, assuming $\phi_0 = \pi/2$, the 0-th oscillator (i=0) is a simple integrator learning the signal offset $\alpha_0(t)$.

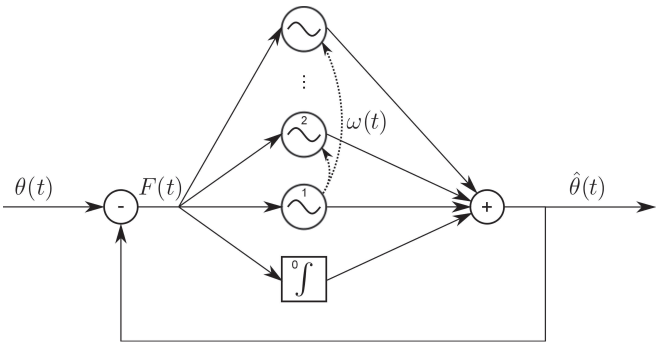

Fig. 3. Coupled adaptive oscillators, learning the harmonics of the input signal $\theta(t)$.

As an illustration, Figure 4 shows the learning of a signal containing an offset and four harmonics with different phase lag. In this example, the adaptive oscillator (2) was initialized with a zero offset, a frequency equal to $\omega = 2\pi$ rad/s, the first harmonic amplitude α_1 equal to 0.05, and the other amplitudes α_i equal to zero.

As shown in the Figure, the signal features are learned after about three seconds. At the end of this learning phase, the oscillator output is sync with the input. To observe this very reactive behavior, the oscillator gains were set to $\nu_\phi = 17.6$, $\nu_\omega = 12.8$ and $\eta = 2$, respectively (see [21] for some synthesis rules for these gains).

C. Adaptive oscillators to learn the vertical node position

The actual vertical position signal of a human walking in the FLOAT is not perfectly periodic, each step being similar but never identical to the previous one. As a consequence, the oscillator features never converge to a steady-state value. To avoid parasitic influences between the learning of the different features, and to make this learning as robust as possible, we decided to decouple the frequency learning from the learning of the other features, and to design a dedicated frequency learning block, being robust to signal variations.

More particularly, we focus on the frequency learning of the node position along the z axis, since this signal is the most sinusoidal of the position signals along the three axis. The method to learn the frequency is described in Section IV-A.

Once the frequency is properly learned, the other features of the actual signal can be learned. Again, this paper focuses

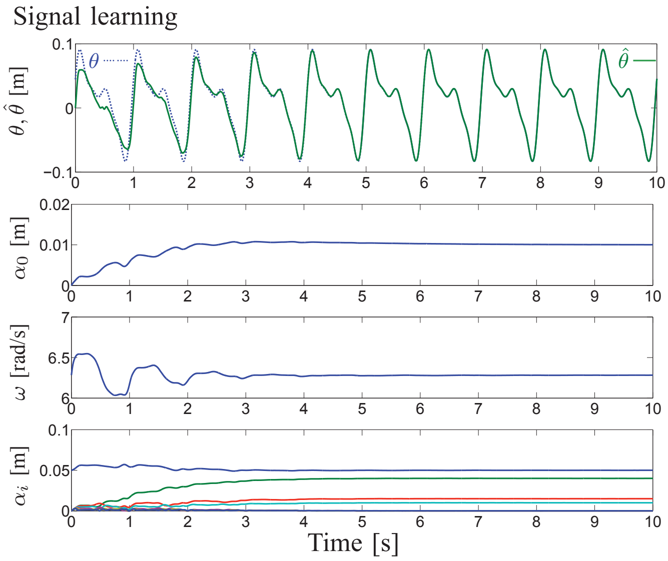

Fig. 4. Signal learning by an adaptive oscillator containing 8 harmonics. After 3 seconds, the state variables have converged to the actual features of the input signal. As expected, only 4 amplitudes converged to non-zero values, since the input signal contained only 4 harmonics (+ offset).

only on the vertical direction, i.e. the position signal along the z-axis. This was done with an adaptive oscillator similar to (2), but receiving the learned frequency ω from the "frequency learning" block rather than estimating it itself.

The next step was to use these learned features to make a prediction of the signal evolution.

The signal was considered to be learned when the error signal $F(t)$ was lower than a tolerance threshold (i.e. 5 mm). When the signal was learned, a prediction was computed, by using similar equations as (1), but with a time lead δ_l:

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

where $\hat{\theta}_{\delta_l}$ denotes the predicted position, with a time lead equal to δ_l. To achieve smooth transitions of the z signal being injected in the "static equilibrium" block between the periods where the signal was learned or not, the signal actually fed to this block was a blend of the actual $z(t)$ and anticipated $\hat{z}(t)$ signal:

$$
z_{blend}(t) = \alpha\hat{z}(t) + (1-\alpha)z(t) \tag{4}
$$

where α varied between 0 and 1. We linearly blended from predicted to current position within 1 s. It increased when the learning was considered as being converged (from the tolerance threshold) and it decreased otherwise. With this method, the output signal staid continuous and the transitions were smooth. Figure 5 shows the result for a prediction of 50 ms. At the beginning, the signal was not learned yet such that the output was equal to the input. When the error went below the threshold, the output smoothly started to anticipate the input.

IV. Experimental protocol

Some experiments were done to validate if the prediction with an adaptive oscillator decreased the force oscillations

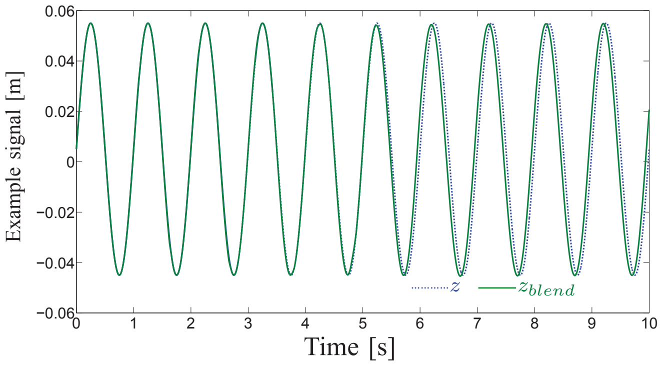

Fig. 5. Smooth blending between current and predicted signal.

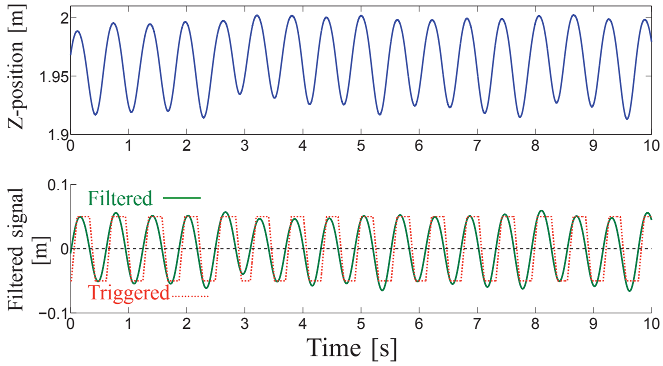

Fig. 6. Z-position oscillations - square signal processing.

in the Z direction. The first experiment consisted in learning the gait frequency independently of other features. The second experiment consisted in registering force oscillations when some healthy subjects were walking with the robot while receiving some body weight support and varying the prediction time δ_l to test its influence on the level of the oscillations.

A. Frequency learning

To extract the frequency information from the z-axis signal in a robust manner, we applied several filters to it, in order to extract its main harmonic as much as possible. First, the signal was filtered with a second-order bandpass filter to eliminate some high-frequency noise and remove the signal offset. The bandpass limit frequencies were chosen at 0 and 1 Hz, such that a simple continuous-time representation of this filter can be obtained as:

$$H(s) = \frac{s}{(s+1)^2} \tag{5}$$

Then the signal was saturated by a nonlinear block that outputs 0.05 if the input is positive and -0.05 if negative, the transitions being governed by finite slopes. This second filter was used in order to normalize the signal amplitude and generate a quasi-square signal at the frequency of the z-axis oscillations. Figure 6 shows the three steps of the signal processing. Importantly, note that filtering and triggering the signal introduced a delay in the square signal with respect to the actual z trajectory. However, this delay did not impact on the learning process, since the signal frequency is not sensitive to it. Various trials and errors let us conclude that the combination of these two filters conducted to the fastest and most robust frequency learning performances.

Thereafter, the frequency of this unbiased square signal was learned with a single adaptive oscillator, i.e. with $K = 1$ and no offset learning in (2).

B. Experiments with human subjects

The goal of the experiment was to establish the positive effect of the prediction during real walking trials. In this case, the natural variability of walking caused the learned frequency to fluctuate. The aim of this experiment was thus to test if the expected decrease in oscillations was observed despite this fluctuation.

Five subjects (two males and three females) with no movement disorder were chosen for the experiment. They age ranged between 25 and 30 years and their weight ranged between 50 and 85 kg. Subjects were asked to walk straight back and forth while attached to the robot. Every 30 seconds, the prediction time of the oscillator was changed. The different tested prediction time values δ_l were 0, 50, 75, 100, 125, 150, 175 and 200 ms. Moreover, the experiment was done with two different virtual body weight supports, i.e. 15 kg and 30 kg.

Oscillations in the force signal were evaluated with the root mean square (RMS) around the reference value of the force. This RMS value was calculated with Equation (6) where n is the number of registered samples:

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(F(i) - F_{ref})^2}{n}} \tag{6}$$

V. Results

A. Frequency learning

The convergence of the oscillator by learning the frequency of real walking data is illustrated in Figure 7. After the subject started walking, the frequency converged in about 5 seconds.

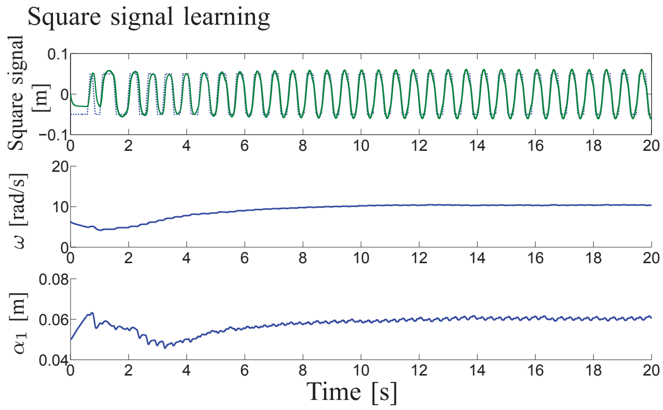

Fig. 7. Frequency learning with 1 harmonic and zero offset.

Importantly, when the subject reached the limit of the robot workspace, he/she had to turn around. During this period, the z signal was no longer periodic and the learning had thus to be interrupted. Of critical importance is to restart the learning without discontinuity in the signal. To achieve this, learning was stopped during a falling edge of the square signal, after the subject had reached the limit threshold in x direction. The learning resumed when the first falling edge appeared after the subject returned inside the x limit range of the robot. With this method, the oscillator resumed the learning with the expected initial conditions after a U-turn and the features convergence was not compromised.

B. Experiments with human subjects

The result with a representative subject are shown in Figure 8.

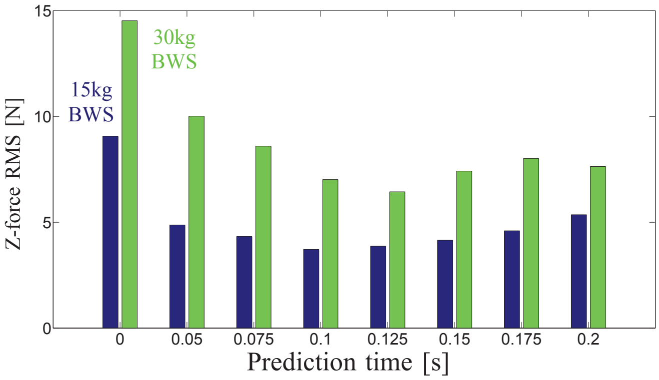

Fig. 8. RMS of the force oscillations along the z-axis recorded during the second experiment, with a representative subject.

As expected, predicting the vertical component of the position signal did decrease the oscillations of the vertical force. The best value for the prediction time (i.e. minimizing the force RMS) was around 100 ms with 15 kg BWS and 125 ms with 30 kg BWS. With these values, oscillations RMS decreased by about 50 % in both cases.

Figure 9 shows the same results for the other four subjects. Interestingly, the RMS decrease was not visible for each subject and/or BWS. The data revealed that the reduction in force error RMS was the most effective when the walking was the most periodic, i.e. when the oscillator achieved the best learning of the features. On top of that, the method worked better with 15 kg BWS than for 30 kg BWS.

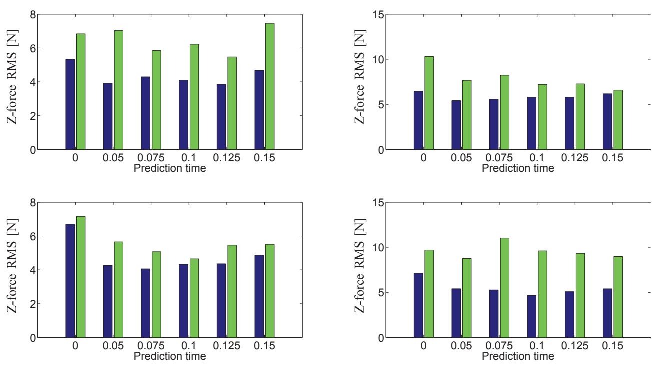

Fig. 9. RMS of the force oscillations along the z-axis recorded during the second experiment, with the other four subjects.

The FLOAT acts like mass/damper system on the user. The parameters identification of this system is explained in [27]. In short, the vertical force felt by the subject was modelled as combining an acceleration-dependent, and velocity-dependent term:

$$F(t) = \hat{m}\ddot{z}(t) + \hat{d}\dot{z}(t) = \hat{m}(\ddot{z}(t) + \hat{\zeta}\dot{z}(t)) \qquad (7)$$

where $\hat{m}$ denotes the estimated mass, and $\hat{d}$ and $\hat{\zeta}$ the absolute and relative damping coefficient. With the original controller, the identified parameters values were equal to $\hat{m} = 6.02\,kg$ and $\hat{d} = 61.6\,\frac{Ns}{m}$. This means that the reflected mass of the robot structure before the force sensor is only $1.02\,kg$, and the main inertia is caused by the mass of the bar and harness construction (weighting about 5 kg), which cannot be compensated with a feedback controller as the original one. This model was also fit to the data with the adaptive oscillator in the loop and with a prediction time equal to 100 ms. The relative damping factor $\hat{\zeta}$ was kept as identified above, and only the mass $\hat{m}$ was re-identified. The best fit was found to be equal to $\hat{m} = 1.71\,kg$, confirming that the reflected inertia of the robot was decreased by a factor 3.5.

VI. Discussion

We identified at least three possible reasons for explaining why some a similar decrease in force oscillations was not observed for all subjects and/or BWS. First, the learning convergence depended on the periodicity of walking, the more periodic the walking, the faster and more robust the learning. Second, the method worked better with 15 kg BWS than for 30 kg BWS, likely because some subjects were too light to accommodate 30kg of BWS. It was indeed difficult for them to walk in this condition, such that their gait was highly variable. Accordingly, future experiments should be realized by providing BWS being proportional to the subject own weight. Finally, the weight of the subject can modify the resonance frequency of the whole system, such that the optimal prediction time would be different from one subject to another. This last point would require more investigations, for example by better identifying the coupled dynamics of the subject and device.

These encouraging results for the Z direction motivate further extension of the concept also to the two other (X and Y) directions. Moreover, the learned frequency should be usable for the three directions, since body oscillations are similar in all three directions. However, this poses additional challenges, mainly because movement is less periodic in these directions. In the X direction, large position slopes are due to the back and forth movements of the subject and thus occlude the oscillations. A similar problem appears in the Y direction, except if the subject walks in a straight line parallel to the x-axis. Although some of our healthy participants managed to do so, this requirement is likely unrealistic in a clinical context. A solution could be to apply a coordinate change, i.e. a rotation to constantly align the x-axis with the walking direction. With this new coordinate system, the Y offset would stay equal to zero, while the x-axis signal would again combine small oscillations and large slopes caused by the forward and backward movements. This axis rotation is possible by equipping the device with a sensor that monitors the current walking direction with respect to the lab frame. With such a mapping, the same method as the one used for the vertical direction can be used for the y-axis. The same frequency as the one learned in the Z direction can be used in the predictor block, although it has to be divided by two. Indeed, lateral oscillations during walking are twice slower than the oscillations in the vertical axis [28].

Cancelling the oscillations along the x-axis would require a more complex predictive block, since the movement slopes would have to be filtered out.

VII. Conclusion

This paper presented a new method to decrease the dynamical effects of a rehabilitation robot felt by the user, and thus increase the robot transparency. The method used to achieve this improvement relied on a trajectory estimator based on an adaptive oscillator. The principle was to add a block in parallel to the robot controller to predict and anticipate the user's movement. When the movement features were learned by the oscillator, it had the capacity to accurately predict the future signal. This prediction, which thus corresponded to the robot position in the near future, can thus be used to anticipate the dynamical effects. Concretely, the method presented here allowed to decrease the force oscillations in the vertical direction by up to 50 %, at least when walking was sufficiently stationary, and for reasonable body weight supports. This result was further validated by an identification process, showing a decrease of the robot equivalent mass by a factor two as well. Future experiments will test the same approach with pathological gaits. Likely, this will require to adapt the method, e.g. to accommodate to the discontinuous gait of patients (e.g. with frequent starts and stops).

References

[1] B. Dehez, J. Sapin, "ShouldeRO, an alignment-free two-DOF rehabilitation robot for the shoulder complex," *12th International Conference on Rehabilitation Robotics (ICORR)*, 2011

[2] T. Nef, M. Guidali, and R. Riener, "Armin iii-arm therapy exoskeleton with an ergonomic shoulder actuation," *Applied Bionics and Biomechanics*, vol. 6, no. 2, pp. 127-142, 2009.

[3] R. Sanchez Jr, E. Wolbrecht, R. Smith, J. Liu, S. Rao, S. Cramer, T. Rahman, J. Bobrow, and D. Reinkensmeyer, "A pneumatic robot for re-training arm movement after stroke: Rationale and mechanical design," *in Rehabilitation Robotics, 2005. ICORR 2005. 9th International Conference on. IEEE*, 2005, pp. 500-504.

[4] A. Stienen, E. Hekman, H. ter Braak, A. Aalsma, F. van der Helm, and H. van der Kooij, "Design of a rotational hydroelastic actuator for a powered exoskeleton for upper limb rehabilitation," *Biomedical Engineering, IEEE Transactions on*, vol. 57, no. 3, pp. 728-735, 2010.

[5] H. Park, Y. Ren, and L. Zhang, "Intelliarm: An exoskeleton for diagnosis and treatment of patients with neurological impairments," *in Biomedical Robotics and Biomechatronics, 2008. BioRob 2008. 2nd IEEE RAS & EMBS International Conference on. IEEE*, 2008, pp. 109-114.

[6] J. F. Veneman, R. Ekkelenkamp, R. Kruidhof, F. van der Helm, and H. van der Kooij, "A Series Elastic- and Bowden-Cable-Based Actuation System for Use as Torque Actuator in Exoskeleton-Type Robots," *Int J Rob Res*, 25(3):261-281, 2006.

[7] J. Pratt, B. Krupp, C. Morse, and S. Collins, "The RoboKnee: An exoskeleton for enhancing strength and endurance during walking," *In Proc IEEE Int Conf Rob Aut (ICRA)*, pp. 2430-2435. 2004.

[8] G. Colombo, M. Joerg, R. Schreier, and V. Dietz, "Treadmill training of paraplegic patients using a robotic orthosis," *Journal of Rehabilitation Research and Development*, 37(6):693-700, 2000.

[9] S. Banala, S. Agrawal, and J. Scholz, "Active Leg Exoskeleton (ALEX) for Gait Rehabilitation of Motor-Impaired Patients," *In Proc IEEE Int Conf Rehab Rob (ICORR)*, pp. 401-407, 2007.

[10] D. Aoyagi, W. E. Ichinose, S. J. Harkema, D. J. Reinkensmeyer, and J. E. Bobrow, "A robot and control algorithm that can synchronously assist in naturalistic motion during body-weight-supported gait training following neurologic injury," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 15(3):387-400, 2007.

[11] G. Kwakkel, B. Kollen, and H. Krebs, "Effects of robot-assisted therapy on upper limb recovery after stroke: a systematic review," *Neurorehabilitation and neural repair*, vol. 22, no. 2, p. 111, 2008.

[12] G. Prange, M. Jannink, C. Groothuis-Oudshoorn, H. Hermens, and M. IJzerman, "Systematic review of the effect of robot-aided therapy on recovery of the hemiparetic arm after stroke," *Journal of rehabilitation research and development*, vol. 43, no. 2, p. 171, 2006.

[13] M. Van der Loos, "Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke," *Arch Phys Med Rehabil*, vol. 83, 2002.

[14] P. Lum, C. Burgar, P. Shor, M. Majmundar, and M. Van der Loos, "Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke," *Arch Phys Med Rehabil*, vol. 83, 2002.

[15] P. Lum, C. Burgar, and P. Shor, "Evidence for improved muscle activation patterns after retraining of reaching movements with the MIME robotic system in subjects with post-stroke hemiparesis," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 12, no. 2, pp. 186-194, 2004.

[16] E. Colgate, and N. Hogan, "An analysis of contact instability in terms of passive physical equivalents," *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, pp. 404-409, 1989.

[17] H. Vallery, A. Duschau-Wicke, and R. Riener, "Optimized Passive Dynamics Improve Transparency of Haptic Devices," *IEEE International Conference on Robotics and Automation*, pp. 301-306, 2009

[18] H. Vallery, A. Duschau-Wicke, and R. Riener, "Generalized Elasticities Improve Patient-Cooperative Control of Rehabilitation Robots," *IEEE 11th International Conference on Rehabilitation Robotics*, pp. 535-541, 2009

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

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

[21] R. Ronsse, S. M. M. De Rossi, N. Vitiello, T. Lenzi, M. C. Carrozza and A. J. Ijspeert, "Real-time estimate of velocity and acceleration of quasi-periodic signals using adaptive oscillators," *IEEE Transactions on Robotics*, in press.

[22] W. Van Dijk, B. Koopman, R. Ronsse, H. Van Der Kooij, "Feed-forward support of human walking," *Biomedical Robotics and Biomechatronics (BioRob), 2012 4th IEEE RAS & EMBS International Conference on*, p. 1955-1960, 2012.

[23] R. Ronsse, S.M.M. De Rossi, N. Vitiello, T. Lenzi, B. Koopman, H. van der Kooij, M.C. Carrozza, A.J. Ijspeert, "Real-time estimate of period derivatives using adaptive oscillators: Application to impedance-based walking assistance," *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, p. 3362-3368, 2012.

[24] R. Ronsse, N. Vitiello, T. Lenzi, J. van den Kieboom, M.C. Carrozza,A.J. Ijspeert, "Human-robot synchrony: flexible assistance using adaptive oscillators," *IEEE transactions on bio-medical engineering*, Vol. 58, no. 4, p. 1001-12, 2011.

[25] 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, A.J. Ijspeert, "Oscillator-based assistance of cyclical movements: model-based and model-free approaches," *Medical & Biological Engineering & Computing*, Vol. 49, no. 10, p. 1173-1185, 2011.

[26] H. Vallery, and P. Lutz, "Apparatus for unloading a user's body weight during a physical activity of said user, particularly for gait training of said user," *European Patent Application EP12154778.0*, 2012.

[27] H. Vallery, P. Lutz, J. von Zitzewitz, G. Rauter, M. Fritschi, Ch. Everarts, R. Ronsse, A. Curt, and M. Bolliger, "Transparent Support for Overground Gait Training," accepted for publication to the *13th International Conference on Rehabilitation Robotics (ICORR)*, 2013

[28] F. Massaad, T.M. Lejeune, C. Detrembleur, "The up and down bobbing of human walking: a compromise between muscle work and efficiency," *J Physiol*, pp. 789-99, 2007.