Compliant Control of a Transfemoral Prosthesis combining Predictive Learning and Primitive-based Reference Trajectories

Sophie Heins and Renaud Ronsse

***Abstract*— This paper reports the development of a novel compliant controller for a transfemoral prosthesis that combines a feed-forward prediction torque component with a feedback error correction. The controller architecture aims to track primitive-based reference trajectories by the prosthetic joints. It relies on Locally Weighted Projection Regression, a function approximator that acts as an inverse internal model of the prosthesis. The proposed strategy is validated in a simulation environment.**

I. INTRODUCTION

Despite the recent progress achieved in research on active lower-limb prostheses, developing efficient control strategies for these devices remains challenging. Given the dynamic nature of human locomotion and the periodic interactions with the environment, it is essential to design compliant control laws to ensure robustness to perturbations [1]. Numerous control methods are being investigated in different devices [1], the most popular combining a finite state machine with impedance control, like in [2]. Other controllers are based on time- or phase-dependent trajectories to be tracked by the prosthetic joints. A recent trend consists in adapting these trajectories to the user in real-time, such as in [3].

In this paper, we outline an adaptive control architecture aiming at tracking continuous, primitive-based reference trajectories. The controller combines predictive learning mechanisms in real-time with feedback error correction. The controller is validated in a simulation environment for normal walking.

II. CONTROL ARCHITECTURE

Our control framework combines predictive learning and primitives-based reference trajectories (see Fig. 1). For each joint of the prosthesis (i.e. the ankle and the knee), compliant position tracking is achieved by combining feedback and feed-forward torque commands (τ_{FB} and τ_{predict} respectively):

$$\tau_{\text{des}} = \tau_{\text{predict}} + \tau_{\text{FB}} \tag{1}$$

This control architecture is bio-inspired, i.e. it mimics the function of the cerebellum in human locomotion. Indeed, the putative role of the cerebellum is twofold: (1) it provides a feed-forward predictive action based on continuous learning of the task, and (2) it provides an error correction action to ensure robustness to perturbations [4],[5].

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A. Generation of Reference Trajectories

For each joint, the reference trajectory θ_{ref} is obtained from a weighted combination of pre-computed Gaussian primitives, similarly as in [6]. These primitives are synchronised with the gait phase, and their weights are modulated as a function of the gait cadence. The gait phase and cadence are estimated in real-time from the hip angle (θ_h) and the ground reaction force (GRF), by means of an adaptive oscillator [7].

B. Feed-forward contribution: Prediction torque

The feed-forward torque component is a prediction torque computed by the inverse internal model of the joint. This inverse model is incrementally learned by Locally Weighted Projection Regression (LWPR), an algorithm that uses local linear models to achieve non-linear function approximation. It has been successfully used as inverse model in different studies performed in a simulation environment, including [8]. In our approach, the LWPR computes τ_{predict} from the inputs $\mathbf{x} = (\text{GRF}, \theta, \dot{\theta}, \theta_{\text{ref}}, \dot{\theta}_{\text{ref}}, \ddot{\theta}_{\text{ref}})$, where θ and $\dot{\theta}$ are the joint position and velocity, and θ_{ref}, $\dot{\theta}_{\text{ref}}$ and $\ddot{\theta}_{\text{ref}}$ are the joint reference position, velocity and acceleration. The prediction torque is a weighted mean of k local linear models $\psi_k(\mathbf{x})$, and the weights $w_k(\mathbf{x})$ are Gaussian functions called receptive fields (RFs):

$$\tau_{\text{predict}}(\mathbf{x}) = \sum_k w_k(\mathbf{x})\psi_k(\mathbf{x}) \tag{2}$$

$$w_k(\mathbf{x}) = \exp\left((\mathbf{x} - c_k)^T D_k(\mathbf{x} - c_k)/2\right) \tag{3}$$

where D_k is the distance metric and c_k is the center of each RF (see [9] for more details about LWPR).

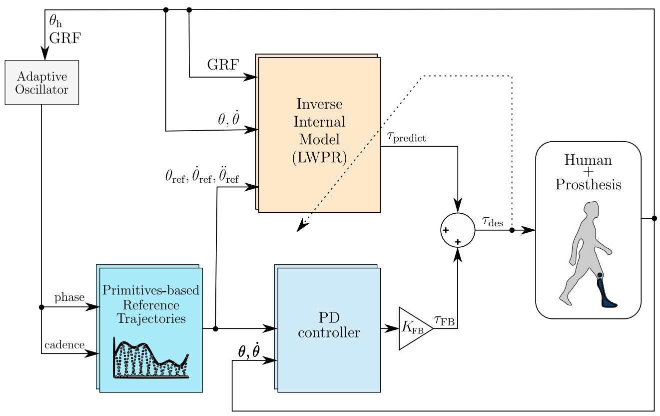

Fig. 1. The control architecture combines adaptive feed-forward (orange) and feedback (blue) torque components for the ankle and the knee joints.

C. Feedback contribution: Error correction

The feedback controller provides error correction following the reference trajectory. It is a proportional-derivative (PD) controller, whose gains K_p and K_d take independent values for the swing phase and for the stance phase (see Table I). The global feedback gain K_{FB} (see Fig. 1) decreases the feedback contribution once the inverse model is learned, in order to increase the controller compliance.

III. SIMULATION RESULTS

We evaluated the performance of the incrementally learned dynamic model in increasing the controller compliance on a simulated biped model. This biped model was developed in the Robotran multibody software [10]. It is composed of 7 rigid bodies (a trunk and 2 segmented leg with foot, shank and thigh), 6 revolute joints that only move in the sagittal plane (ankle, knee and hip of both legs), and 1 prismatic joint that only moves in the vertical direction (the center of mass). In the ground contact model, only the vertical component of the GRF is modelled, and its computation is based on [11]. The hip, knee and ankle joints of the left leg and the hip joint of the right leg are forced to follow Winter angle trajectories for normal walking [12]. The control architecture presented in Section II is implemented on the knee and ankle joints of the right leg.

Results of the simulation showed that the LWPR was able to rapidly learn the inverse model of both joints and provided an accurate torque prediction after a few cycles only. The evolution of the contribution of the feedback torque component to the total joint torque per cycle is provided in Fig. 2, for both joints. We can see that it quickly converges to 30% for the ankle joint and 18% for the knee joint. Then, the gains of the PD controller were reduced after 50 cycles, i.e. K_{FB} was set to 50% for the ankle joint and to 5% for the knee joint. This further decreased the feedback contribution to the total torque to 28% and 6% for the ankle and the knee respectively, without altering the tracking accuracy. Indeed, the RMSE of the ankle and knee angles remained under 2% and 1% of the maximum angular amplitude respectively. This lead to compliant position tracking.

IV. DISCUSSION AND CONCLUSION

We developed a bio-inspired, compliant controller for a transfemoral prosthesis that mimics the role of the cerebellum in human locomotion. The controller combines a feed-forward prediction torque command with a feedback error correction mechanism. The feed-forward action uses the LWPR algorithm, acting as an inverse internal model of the system. We validated the proposed approach on a simple biped model in a simulation environment. Results showed that the LWPR is able to quickly learn the inverse model of each joint and provides accurate torque commands in real-time. This allows to decrease the PD gains of the feedback action, leading to a more compliant position tracking. Future work includes the validation of this control architecture on a real transfemoral prosthesis.

TABLE I
CONTROLLER GAINS

Joint	K_p (Nm/rad)		K_d (Nms/rad)	
	Stance	Swing	Stance	Swing
Knee	6000	1000	200	25
Ankle	5000	150	15	1.3

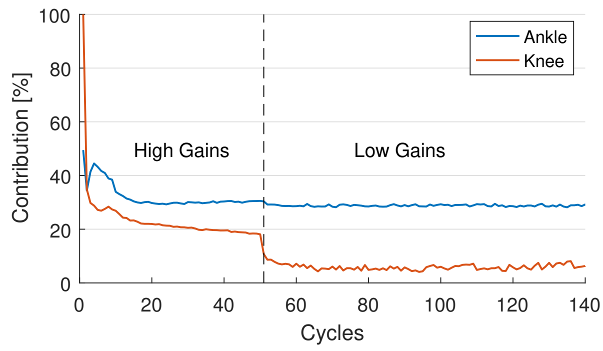

Fig. 2. The feedback torque contribution to the total joint torque per cycle rapidly decreases while the inverse internal model is learned, for both joints.

REFERENCES

[1] M. R. Tucker, J. Olivier, A. Pagel, H. Bleuler, M. Bouri, O. Lambercy, J. d. R. Milln, R. Riener, H. Vallery, and R. Gassert, "Control strategies for active lower extremity prosthetics and orthotics: a review," *Journal of NeuroEngineering and Rehabilitation*, vol. 12, no. 1, 2015.

[2] F. Sup, A. Bohara, and M. Goldfarb, "Design and Control of a Powered Transfemoral Prosthesis:," *The International Journal of Robotics Research*, Feb. 2008.

[3] R. W. Jackson and S. H. Collins, "Heuristic-Based Ankle Exoskeleton Control for Co-Adaptive Assistance of Human Locomotion," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 10, pp. 2059–2069, 2019.

[4] I. Saunders and S. Vijayakumar, "The role of feed-forward and feedback processes for closed-loop prosthesis control," *Journal of NeuroEngineering and Rehabilitation*, vol. 8, p. 60, Oct. 2011.

[5] I. Pisotta and M. Molinari, "Cerebellar contribution to feedforward control of locomotion," *Frontiers in Human Neuroscience*, vol. 8, June 2014.

[6] S. Heins, L. Flynn, H. Laloyaux, J. Geeroms, D. Lefeber, and R. Ronsse, "Compliant Control of a Transfemoral Prosthesis by combining Feed-Forward and Feedback," *2020 8th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, 2020. Accepted for publication.

[7] T. Yan, A. Parri, V. Ruiz Garate, M. Cempini, R. Ronsse, and N. Vitiello, "An oscillator-based smooth real-time estimate of gait phase for wearable robotics," *Autonomous Robots*, vol. 41, pp. 759–774, Mar. 2017.

[8] S. Tolu, M. Vanegas, N. R. Luque, J. A. Garrido, and E. Ros, "Bio-inspired adaptive feedback error learning architecture for motor control," *Biological Cybernetics*, vol. 106, pp. 507–522, Oct. 2012.

[9] S. Vijayakumar, A. D'Souza, and S. Schaal, "Incremental online learning in high dimensions," *Neural computation*, vol. 17, pp. 2602–34, 01 2006.

[10] N. Docquier, A. Poncelet, and P. Fisette, "Robotran: a powerful symbolic gnerator of multibody models," *Mechanical Sciences*, vol. 4, no. 1, pp. 199–219, 2013.

[11] 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*, Jan. 2018.

[12] D. A. Winter, *The biomechanics and motor control of human gait*. University of Waterloo Press, Sept. 1987.