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DOI

[10.1007/978-3-030-64313-3_2](https://doi.org/10.1007/978-3-030-64313-3_2)

Publication date

2021

Document Version

Final published version

Published in

Biomimetic and Biohybrid Systems

Citation (APA)

Angelini, F., Bianchi, M., Garabini, M., Bicchi, A., & Santina, C. D. (2021). Iterative learning control as a framework for human-inspired control with bio-mimetic actuators. In V. Vouloutsi, A. Mura, P. F. M. J. Verschure, F. Tauber, T. Speck, & T. J. Prescott (Eds.), *Biomimetic and Biohybrid Systems : Proceedings of the 9th International Conference, Living Machines 2020* (pp. 12-16). (Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics); Vol. 12413 LNAI). Springer. https://doi.org/10.1007/978-3-030-64313-3_2

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Iterative Learning Control as a Framework for Human-Inspired Control with Bio-mimetic Actuators

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Abstract. The synergy between musculoskeletal and central nervous systems empowers humans to achieve a high level of motor performance, which is still unmatched in bio-inspired robotic systems. Literature already presents a wide range of robots that mimic the human body. However, under a control point of view, substantial advancements are still needed to fully exploit the new possibilities provided by these systems. In this paper, we test experimentally that an Iterative Learning Control algorithm can be used to reproduce functionalities of the human central nervous system - i.e. learning by repetition, after-effect on known trajectories and anticipatory behavior - while controlling a bio-mimetically actuated robotic arm.

Keywords: Motion and motor control · Natural machine motion · Human-inspired control

1 Introduction

Natural and bio-inspired robot bodies are complex systems, characterized by an unknown nonlinear dynamics and redundancy of degrees of freedom (DoFs). This poses considerable challenges for standard control techniques. For this reason, researchers started taking inspiration from the effective Central Nervous System (CNS), when designing controllers for robots [4, 5]. In this work, we test experimentally a model-free controller intended for trajectory tracking with biomimetic robots. We prove that the required tracking performances can be matched, while presenting well-known characteristics of human motor control system, i.e. learning by repetition, mirror-image aftereffect, and anticipatory behavior. We do that by presenting experiments on a robotic arm with two degrees of freedom, each of which is actuated by means of a bio-mimetic mechanism replicating the behavior of a pair of human muscles [7] (Fig. 1(a)).

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V. Vouloutsi et al. (Eds.): Living Machines 2020, LNAI 12413, pp. 12–16, 2020.

https://doi.org/10.1007/978-3-030-64313-3_2

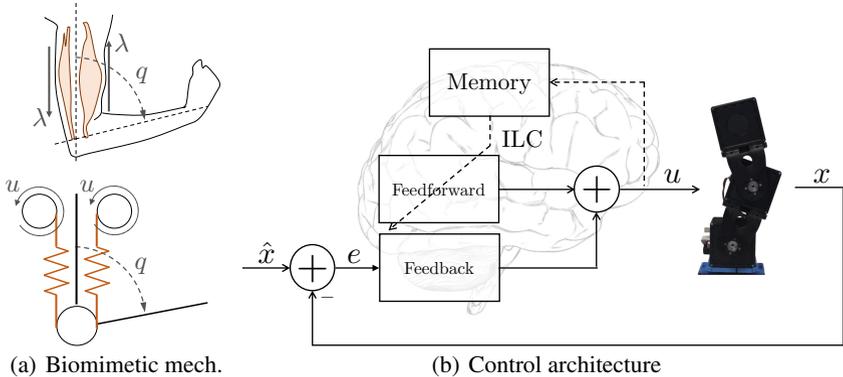


Fig. 1. The synergy between human musculoskeletal system and the CNS can be imitated by a bio-mimic robot and a proper controller mixing anticipatory (feedforward) and reactive (feedback) actions.

2 From Motor Control to Motion Control

Taking inspiration from the human CNS, we aim at designing a controller able to replicate the characteristics of *paleokinetic level* of Bernstein classification [2]. This provides reflex function and manages muscle tone, i.e. low level feedback and dynamic inversion. We want to do that by reproducing salient features observed in humans.

Learning by repetition [10] (behavior (i)) is the first feature we are interested into. CNS is able to invert an unknown dynamics over a trajectory, just by repeating it several times. This is clear in experiments where an unknown force field is applied to a subject's arm, and she or he is instructed to sequentially reach to track a point in space. In every repetition the tracking is improved until an almost perfect performance is recovered.

Anticipatory behavior [8] (behavior (ii)) is the second characteristic we want to reproduce. The CNS can anticipate the necessary control action relying on motor memory, rather than always reacting to sensory inputs. In control terms this means relying more on feed-forward than on feedback. In humans this characteristic tends to appear more strongly when the motor memory increases.

Finally, humans present aftereffect over a learned trajectory [9] (behavior (iii)). By removing the force field, subjects exhibit deformations of the trajectory specular to the initial deformation due to the force field introduction. This behavior is called mirror-image aftereffect and is the third characteristic we aim at reproducing.

Figure 1(b) shows the control architecture. We suppose no a priori knowledge of system dynamics. We just read the joint evolution and velocity $x \in \mathbb{R}^{2n}$, and we produce a motor action $u \in \mathbb{R}^n$. The purpose of the controller is to perform dynamic inversion of the system, i.e. computing the control action $\hat{u} : [0, t_f] \rightarrow \mathbb{R}^m$ able to track a given desired trajectory $\hat{x} : [0, t_f] \rightarrow \mathbb{R}^{2n}$. This has to be

done by repeating several times the same task and performing it better each time (learning by repetition). To implement this feature, we propose a control law based on Iterative Learning Control (ILC) [3]: $u_{i+1} = u_i + \Gamma_{FFP} e_i(t) + \Gamma_{FFd} \dot{e}_i(t) + \Gamma_{FBP} e_{i+1}(t) + \Gamma_{FBd} \dot{e}_{i+1}(t)$. We call u_i and $e_i \triangleq \hat{x} - x_i$ the control action and the error at the i -th repetition of the task. $\Gamma_{FFP} \in \mathbb{R}^{m \times 2n}$ and $\Gamma_{FFd} \in \mathbb{R}^{m \times 2n}$ are the PD control gains of the iterative update while $\Gamma_{FBP} \in \mathbb{R}^{m \times 2n}$ and $\Gamma_{FBd} \in \mathbb{R}^{m \times 2n}$ are the PD feedback gains. We analyzed the theoretic control implications of using similar algorithms in [1, 6].

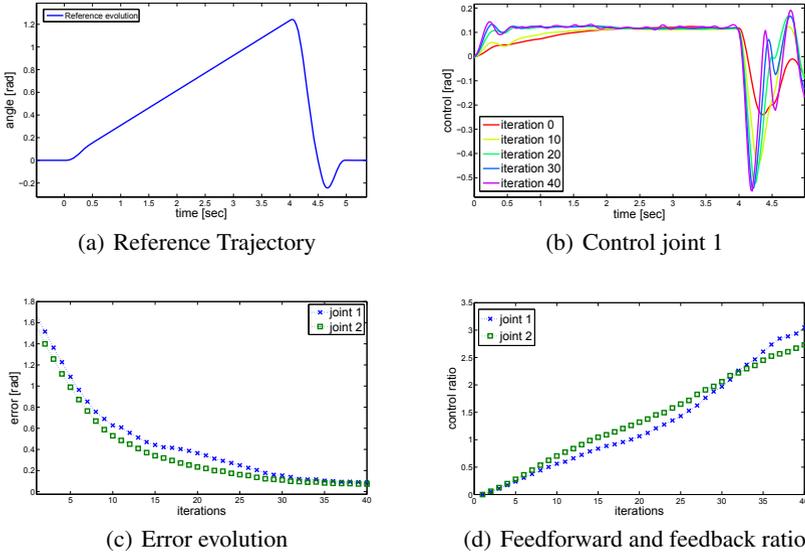


Fig. 2. Experimental results. (a) shows the reference trajectory. (b) reports the evolution of control input at joint 1. (c) shows the error over 40 iterations (behavior (i), learning by repetition). (d) depicts the ratio between reactive and anticipatory actions (behavior (ii)).

3 Experimental Results

The goal of the experiments is to prove that the considered ILC-based algorithm can reproduce the discussed human-like behaviors when applied to a biomimetic hardware. The algorithm is applied to a two degrees of freedom planar arm, with bio-mimetic actuation. More specifically, the mechanism mimics a pair of human muscles. The available control input u has been proven to be equivalent to the corresponding signal in λ -model of human muscles [7]. We consider the following gains for the algorithm Γ_{FFP} is $\text{blkdiag}([1, 0.1], [1.25, 0.0375])$, Γ_{FFd} is $\text{blkdiag}([0.1, 0.001], [0.0375, 0.001])$, Γ_{FBP} is $\text{blkdiag}([0.25, 0.025], [0.25, 0.025])$, and Γ_{FBd} is $\text{blkdiag}([0.025, 0.001], [0.025, 0.001])$. The desired trajectory (same for both joints)

is shown in Fig. 2(a). Note that this is a very challenging reference, having large amplitudes and abrupt changes in velocities. For performance evaluation we use norm 1 of the tracking error. The proposed algorithm learns the task by repeating it 40 times achieving good performance. Figure 2(b) shows the joint 1 control evolution for some meaningful iterations (similar results apply to joint 2). Figure 2(c) proves that the system implements learning by repetition (behavior (i)), reducing the error exponentially to 0 by repeating the same movement. Figure 2(d) depicts the ratio between total feedforward and feedback action, over learning iterations. This shows the predominance of anticipatory action at the growth of sensory-motor memory (behavior (ii)). It is worth to be noticed that feedback it is not completely replaced by feedforward, which is coherent with many physiological evidences (e.g. [10]).

To test the presence of mirror-image aftereffect (behavior (iii)) we introduced an external force field after the above discussed learning process. This field was generated as shown by Fig. 3(a), by two springs connected in parallel to the second joint. Figure 3(b) shows the robot's end effector evolution obtained before (green) and after (red) spring introduction. The algorithm can recover the original performance after few iterations (learning process not shown for the sake of space). Finally the springs are removed, and the end-effector follows a trajectory which is the mirror w.r.t. the nominal one, of the one obtained after field introduction, therefore proving the ability of the proposed algorithm to reproduce mirror-image aftereffect (behavior (iii)).

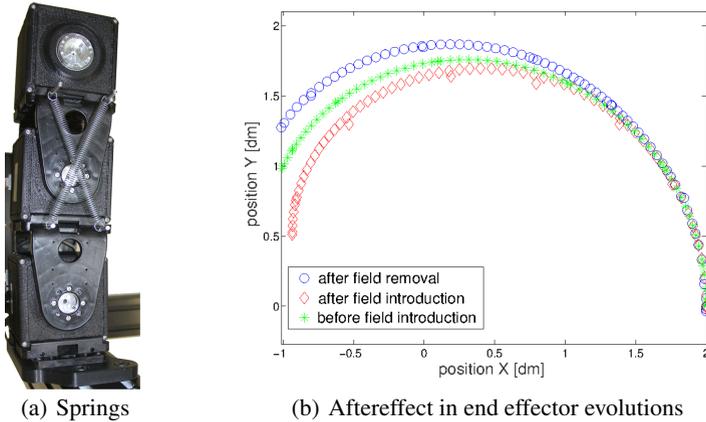


Fig. 3. The proposed controller presents aftereffect (behavior (iii)). Panel (a) reports the spring interconnection implementing the unknown force field, and Panel (b) end effector evolutions. (Color figure online)

4 Conclusions

In this work we proved experimentally that an ILC-based algorithm can reproduce - when applied to a biobimetic hardware - several behaviors observed when the central nervous system controls the muscle-skeletal system - namely learning by repetition, experience-driven shift towards anticipatory behavior, and after-effect.

Acknowledgments.. This project has been supported by European Union’s Horizon 2020 research and innovation programme under grant agreement 780883 (THING) and 871237 (Sophia), by ERC Synergy Grant 810346 (Natural BionicS) and by the Italian Ministry of Education and Research (MIUR) in the framework of the CrossLab project (Departments of Excellence).

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