Model-Free Torque Iterative Learning Control for Resilient and Stable Physical Interaction of Articulated Soft Robots

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***Abstract*— Modern robotic applications often involve physical interactions between the robot's end-effector and the environment. Such operations may lead to stability and resilience issues if the Cartesian impedance is not properly tuned. This means that there are bounds for the impedance value related to some characteristics of the interaction such as surface geometry, the number of uncertainties, and the contact forces. In the case of robots which present fixed or variable elasticity at the joints, i.e., articulated soft robots (ASRs), the impedance value can be set tacking into account these bounds. However, the problem of separately controlling the stiffness while maintaining a good trajectory tracking is still challenging. In this paper we present a controller for ASRs based on Iterative Learning Control that allows achieving this result, i.e., to obtain a good tracking performance and to impose the desired robot compliance. Then, we present a method to define the impedance bounds that allow performing a stable and resilient interaction with the environment. The proposed method has been validated through a button pushing task.**

I. Introduction

Manipulation, cooperation, polishing, grasping are just a few examples of tasks where robotic systems have to make contact with the environment. During these operations, the main features we should focus on are robustness, robot resilience, and interaction stability. Indeed, uncertainties, contact surface shapes, and interaction forces may alter the stability and the integrity of the robot [1], [2]. To avoid these issues, the Cartesian stiffness should be properly tuned. In particular, there exists an upper bound on the stiffness that prevents exchanging high forces to guarantee adaptability and safety. Despite this, however, there is also a lower bound that guarantees the stability of such interactions.

Articulated soft robots [3] are systems with elasticity lumped at the joints that allow safe and robust interactions with human beings and the environment. In particular, robots actuated by Variable Stiffness Actuators (VSAs) [4] (Fig. 1) allow to mechanically change the joint compliance. However, controlling VSA robots is not a trivial task. Moreover, Classical control techniques that rely on high-gain feedback terms lead to an undesired alteration of the robot elasticity [5]. For this reason, novel approaches able to achieve motion tracking while preserving the elastic structure of the system have been proposed [6]. Furthermore, articulated soft robots usually present a nonlinear and hard-to-model dynamics that limits the applicability of model-based approaches.

This research has received funding from the European Union's Horizon 2020 Research and Innovation Programme under Grant Agreement No. 732737 (ILIAD), No. 780883 (THING), and No. 871237 (SOPHIA).

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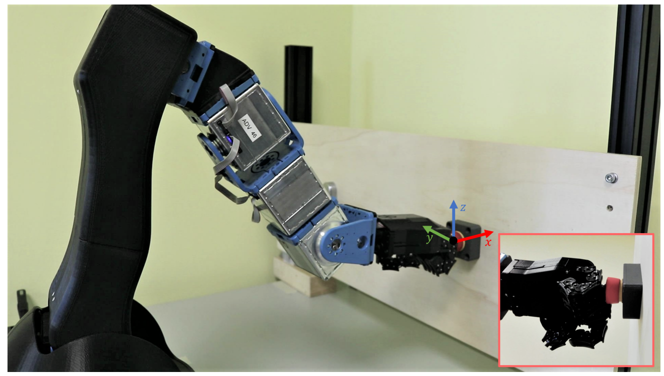

Fig. 1. A 6-DoFs articulated soft robotic arm equipped with variable stiffness actuators (VSAs) executing a button pushing task.

Conversely, model-free feedforward approaches do not present these drawbacks. Iterative Learning Control (ILC) has shown promising results [5]. This allows us to improve tracking performance through repetitions of the same task, without requiring an accurate model representation. However, learning-based approaches present issues in terms of scalability and generalization of the learned control actions. This means that each desired task requires a different learning phase. The literature proposes solutions to limit the number of required learning processes. In [7] it is studied the problem of generalizing the acquired control inputs w.r.t. velocity execution. In [8] it is studied the generalization w.r.t. the desired stiffness profile. Finally, in [9] it is studied the generalization w.r.t. the space trajectory.

In addition, learning a task that involves physical interaction with the environment may lead to damages to the robot structure if the stiffness is to high. For this reason, in this paper, we present also the Cartesian stiffness bounds that must be verified to achieve a resilient and stable interaction, and we design a controller able to execute the desired task.

Experimental results show that the proposed controller allows learning the task with a soft behavior. Once learned, the stiffness behavior can be changed to a stiffer setup, taking into account the stability and resilience bounds, in order to successfully accomplish the task.

II. PROPOSED APPROACH

We here consider the dynamic model of an n-Degrees of Freedom (DoFs) VSA robot

$$\begin{cases} M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)+\dfrac{\partial V(q,\theta)^T}{\partial q}=\tau_{\text{ext}}, & (1)\\ J\ddot{\theta}+D\dot{\theta}+\dfrac{\partial V(q,\theta)^T}{\partial \theta}=\tau_{\text{m}}, & (2)\end{cases}$$

where $q\in\mathbb{R}^n$ are the link positions; $\theta\in\mathbb{R}^m$ are the motor positions; $M(q)$ and $C(q,\dot{q})$ are inertia and Coriolis, centrifugal and frictional terms, respectively, and $G(q)$ is the gravitational vector of the system. J, D are inertia and damping constant diagonal matrices of the motors; $V(q,\theta)$ is the elastic potential; τ_{m} are the motor torques and τ_{ext} is the external torque. We define with $J(q)$ the Jacobian matrix that is useful for computing the Cartesian stiffness matrix starting from the stiffness of the joints as follows

$$K=J(q)^{-T}K_jJ(q)\ , \tag{3}$$

where $K_j=\text{diag}([\sigma_1,...,\sigma_n])$ is the stiffness matrix, with joint stiffness elements σ_i.

A. Cartesian stiffness bounds

We model the interaction between the end-effector of the robot and the environment and we study its linearization [10]. The contact surface profile can be locally approximated by a sphere with constant radius R. We assume to be able to control the end-effector reference position $\bar{x}_c$ and to modulate its Cartesian impedance along the x,y and z axes. We assume that the maximum allowed force to avoid damages to the robot is F_{max}, and that to execute the task there is a minimum required force F_{min}. We also hypothesize that there are uncertainties Δx along the x direction. From the stability and resilience analysis in [10] we conclude that the bounds on the Cartesian stiffness components K_{x} and $K_{\text{y,z}}$ are given by

$$K_{\text{x}}>\frac{F_{\text{min}}}{|\bar{x}_{\text{c}}+\Delta_x-R\cos(\alpha)|}\ , \tag{4}$$

$$K_{\text{x}}<\frac{F_{\text{max}}}{|\bar{x}_{\text{c}}-\Delta_x-R\cos(\alpha)|}\ , \tag{5}$$

$$K_{\text{y,z}}>\frac{F_{\text{x}}}{R}\ , \tag{6}$$

where α is angular position of the contact point. K_{x} presents the lower bound (4) required by the task specifications. K_{x} presents the upper bound (5) required to avoid any damage. $K_{\text{y,z}}$ present the lower bounds (6) required to preserve stability. $K_{\text{y,z}}$ do not have an upper bounds. The interested reader can refer to [10] for further details.

B. Model-free iterative learning control

The control input τ_{m} can be decoupled into an equilibrium control input τ_{eq}, which defines the link motion, and a stiffness regulation input τ_{sr}, which sets the robot stiffness profile [8]. Relying on this result, we separately define the two control inputs. τ_{sr} is a proportional integral (PI) controller tracking the desired stiffness profile $\hat{\theta}_{\text{sr}}$

$$\tau_{\text{sr}}=k_{\text{p}}(\hat{\theta}_{\text{sr}}-\theta_{\text{sr}})+k_{\text{i}}\int(\hat{\theta}_{\text{sr}}-\theta_{\text{sr}})\text{d}t\ , \tag{7}$$

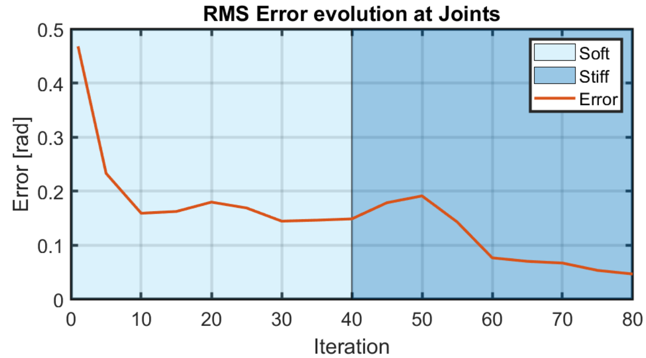

Fig. 2. Root Mean Square (RMS) of the error over iterations. 40 iterations are executed with a soft behavior to avoid damage to the robot and the environment during learning. After the stiffness modification, we executed 40 more iterations to further improve tracking performance.

where $k_{\text{p}},k_{\text{i}}\in\mathbb{R}$ are the proportional and integral gains.

For the link motion, we adopt an ILC-approach. Given a desired link trajectory (with final time t_{f}), the iteratively learned control action τ_{eq}, at iteration $k\in\mathbb{N}^+$, combines a FeedForward (FF) and a FeedBack (FB) component, namely τ_{FF}^k and τ_{FB}^k, such that

$$\tau_{\text{eq}}^k(t)=\underbrace{\tau_{\text{eq}}^{k-1}(t)+K_{\text{UP}}(t)\xi^{k-1}(t)}_{\tau_{\text{FF}}^k(t)}+\underbrace{K_{\text{FB}}(t)\xi^k(t)}_{\tau_{\text{FB}}^k(t)}\ , \tag{8}$$

where ξ^k is the joint position and velocity tracking error at iteration k and $K_{\text{UP}},K_{\text{FB}}$ are the update and feedback control gain matrices, respectively.

It is worth noting that the control law (8) is model-free and preserves the robot compliant behavior since it is mostly feedforward (K_{FB} are set low) [5]. Further details about the input decoupling property, the control algorithm, and the convergence of the iterative method can be found in [8].

III. EXPERIMENTAL VALIDATION

To validate the proposed approach we employ a 6-DoFs manipulator actuated by VSA qbmoves Advanced [11], that has to perform an interaction task (Fig. 1). The task is a button pushing operation. In order to press the button, the manipulator has to exert a minimum force $|F_{\text{min}}|\geq 22\,\text{N}$, while a maximum allowed force is $F_{\text{max}}=40\,\text{N}$. The radius of curvature of the button surface is $R=0.0725\,\text{m}$ and uncertainties up to $\Delta_x=\pm0.01\,m$ are considered. This leads to the following bounds for the Cartesian stiffness along the contact surface $352\,\text{N/m}<K_{\text{x}}<485\,\text{N/m}$, and on the tangential plane $K_{\text{y,z}}>303\,\text{N/m}$, according to Sec. II-A.

The desired trajectory has been shown to the robot manually moving its end-effector. We applied the controller proposed in Sec. II-B. In order to avoid damages of the robot during the learning process we executed 40 iterations with a soft behavior, i.e., $\hat{\theta}_{\text{sr}}=0.12\,\text{rad}$ for each joint. Then, we switched the desired behavior to a stiffer one ($\hat{\theta}_{\text{sr}}=0.48\,\text{rad}$), without changing the control input leveraging the decoupling property of the controller. We executed 40 more iterations to further improve tracking performance. Fig. 2 shows the Root Mean Square (RMS) of the error over iterations. The results

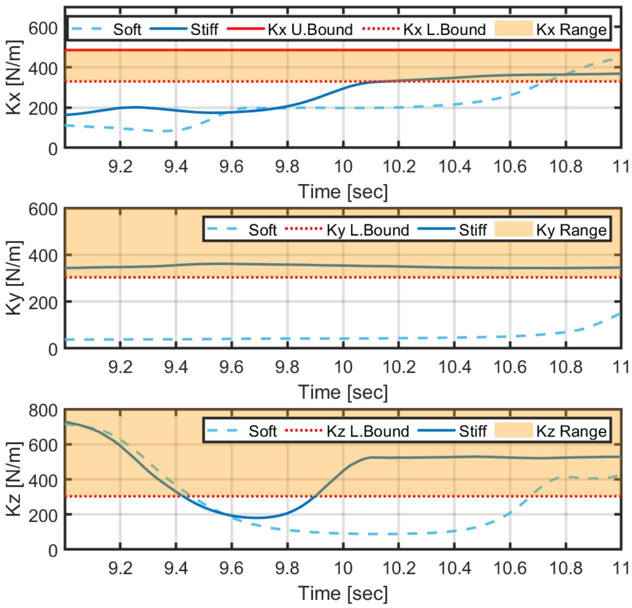

Fig. 3. Cartesian stiffness in the soft and the stiff configuration. The contact occurs approximately at 10 sec. The soft case does not verify the bounds (4)-(6).

show that the controller allows achieving a low tracking error with both soft and stiff behaviors.

Despite this, the stiffness profile with the soft configuration does not satisfy the required bounds (4), (5), (6), as visible in Fig. 3. Thus, even if the robot is able to track the trajectory needed to perform the task (Fig. 4), after the contact occurs (approximately at 10 sec) the performance degrades because the robot end-effector slips over the button (Fig. 4).

Differently, with a stiffer configuration the stiffness bounds at the contact moment are satisfied (Fig. 3). As a result of this, the robot is now able to successfully execute the button pushing task maintaining a low error at the joints (Fig. 4).

IV. Conclusions

In this work, we presented a control algorithm able to separately control the motion and the stiffness of an articulated soft robot based on iterative learning. In addition to this, we introduced a method to evaluate the bounds on the Cartesian impedance that aim to obtain a resilient and stable interaction between the robot end-effector and the environment in case of uncertain interaction scenarios. The conjunction of these two approaches allows us to firstly learn the desired joint trajectory safely. Then, once the trajectory has been learned, the joint stiffness can be adjusted without compromising the trajectory at the joints and in order to verify the bounds on the Cartesian impedance required to correctly execute the task. The proposed method has been validated through an experiment on a 6-DoFs articulated soft robot performing a button pushing task.

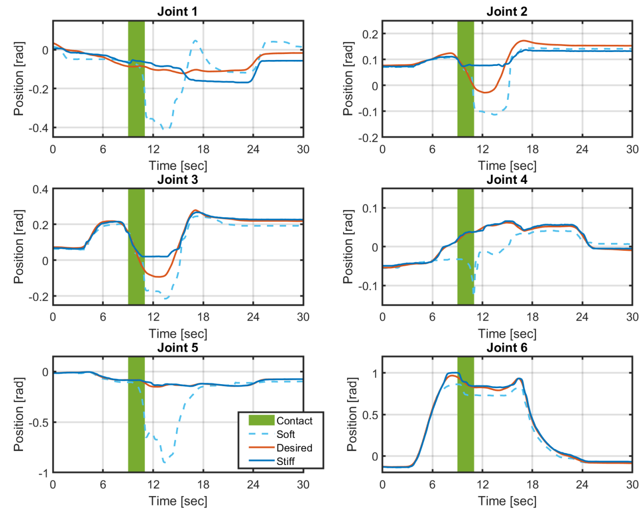

Fig. 4. The joint trajectory in the soft and the stiff configuration at the end of the learning process. The soft configuration does not verify the bounds on the Cartesian stiffness. This leads to slippage and a failure of the task. Conversely, the stiff configuration verifies the bounds and successfully execute the task.

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