A Fast and Reliable Pick-and-Place Application with a Spherical Soft Robotic Arm

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Abstract— This paper presents the application of a learning control approach for the realization of a fast and reliable pick-and-place application with a spherical soft robotic arm. The arm is characterized by a lightweight design and exhibits compliant behavior due to the soft materials deployed. A soft, continuum joint is employed, which allows for simultaneous control of one translational and two rotational degrees of freedom in a single joint. This allows us to axially approach and pick an object with the attached suction cup during the pick-and-place application. An analytical mapping based on pressure differences and the antagonistic actuator configuration is introduced, allowing decoupling of the system dynamics and simplifying the modeling and control. A linear parameter-varying model is identified, which is parametrized by the attached load mass and a parameter related to the joint stiffness. A gain-scheduled feedback controller is proposed, which asymptotically stabilizes the robotic system for aggressive tuning and over large variations of the parameters considered.

The control architecture is augmented with an iterative learning control scheme enabling accurate tracking of aggressive trajectories involving set point transitions of 60 degrees within 0.3 seconds (no mass attached) to 0.6 seconds (load mass attached). The modeling and control approach proposed results in a reliable realization of a pick-and-place application and is experimentally demonstrated.

I. INTRODUCTION

Pneumatically actuated soft robotic systems show promise for a variety of applications due to their intrinsic properties [1], [2], [3]. In particular, the inherent compliance and the low weight make these robotic systems safer compared to rigid manipulators and allow them to be deployed beside humans without presenting any danger [4], [5]. The combination of low inertia and pneumatic actuation enables fast actuation as shown in [6] and [7].

By arranging multiple actuators antagonistically around a joint, both stiffness and position can be controlled independently [8]. The simultaneous position and stiffness control of a fully inflatable soft robotic arm with a single degree of freedom is presented in [9]. An approach to adjust the stiffness of a spherical robotic arm combining two degrees of freedom in a single joint is presented in [10].

Pneumatically actuated soft robotic systems often exhibit complex dynamics due to the viscoelastic material behavior [2]. For the purpose of feedback controller synthesis, it is a common strategy to rely on low-complexity models and compensate for uncertainty by feedback. A linear time-invariant model is identified in [7] and used in an Iterative Learning Control (ILC) scheme to ensure accurate tracking for aggressive trajectories. The authors of [11] synthesize a gain-scheduled feedback controller for reference tracking based on a Linear Parameter-Varying (LPV) system. The control system is further augmented with an ILC scheme. The application of ILC to improve the tracking performance and preserve the compliance of the system at the same time is presented in [12].

In terms of pick-and-place applications with soft robotic systems, a grasp-and-place operation using a planar manipulator consisting of a series of fluidic arm segments is outlined in [13]. A pick-and-place application is described in [14] using a soft robotic arm consisting of a series of antagonistically actuated single degree of freedom inflatable segments. In [15], a grabbing task based on ILC is implemented on a soft spatial fluidic elastomer manipulator. Continuum robots for object manipulation are documented in [16] and [17].

In this work, we present the realization of a pick-and-place application using the antagonistically actuated spherical soft robotic arm depicted in Fig. 1. Two rotational and one translational or stiffness degree of freedom can be simultaneously controlled in a single joint based on the continuous structure of the soft joint.

First, a mapping based on pressure differences and the antagonistic actuation principle of the system is used to decouple the plant dynamics, simplifying the modeling and control. An LPV model is identified, capturing the influence of the load mass and a parameter which is related to the stiffness of the joint. A gain-scheduled feedback controller is designed, which relies on the parameter-varying dynamics
and ensures robustness over a large range of the parameters considered. This property is validated by manipulating an object with similar weight to the movable part of the soft robot. As pick-and-place applications are often repetitive in nature, an ILC scheme is proposed to enable accurate tracking of aggressive maneuvers. Simultaneous elongation and angle control, leveraging the compliance of the soft joint, are shown as required when picking an object with the suction cup. While applications with soft robotic systems are typically slower than classical robotic systems, we demonstrate that a fast pick-and-place application can reliably be realized using the modeling and control approach presented.

The remainder of this paper is organized as follows: The soft robotic platform is briefly described in Section II. A mapping based on pressure differences to decouple the plant dynamics is introduced in Section III. The identification of the LPV model is presented in Section IV and the design of a gain-scheduled feedback controller and an ILC scheme is outlined in Section V. The realization of the pick-and-place application is discussed in Section VI, and a conclusion is drawn in Section VII.

II. SOFT ROBOTIC ARM

In this section, the spherical soft robotic arm used for the pick-and-place application is described.

The soft robotic arm consists of six main components: a static link, a movable link, a soft joint, three bellows type actuators, a vacuum gripper as an end effector and a base plate for mounting the system (see Fig. 1). The static and movable links are based on a double-shell design, consisting of an inflatable, airtight inner bladder and a sewn, inextensible outer shell. These result in a lightweight construction, where the mass of the movable link is given by 200 g. Pressurization of the links provides the structural stability of the robot arm. The soft joint connects the movable with the static link and is symmetrically enclosed by the actuator triplet, as depicted in Fig. 2 (right). The design is based on previous work presented in [10], with several components and properties of the system being optimized to provide the mechanical robustness required for the realization of a pick-and-place application. This particularly applies to the actuator design. The maximum burst pressure of the actuators is increased from 2.2 to 6.0 bar by using a material with high tensile strength and a more sophisticated manufacturing process based on high-frequency welding. Furthermore, the joint system of the soft robotic arm is optimized. Differently to the previous system, which relied on a rigid ball-and-socket joint, a soft joint made from silicone rubber (Wacker Elastosil® M 4641) is used, enabling large deformations. This allows for an extension of the angular range from $\theta = 45^\circ$ to $75^\circ$, routing the tubing internally and introducing a controllable, translational degree of freedom (see Fig. 2 left). The additional degree of freedom is a key feature when picking an object in a pick-and-place application, as it enables axially approaching the object with the suction cup.

The combination of the soft joint and the antagonistic configuration of the three actuators allows for the control of two rotational degrees of freedom and the independent control of either the overall joint stiffness or the axial elongation in a single joint. Notice that an increase in the overall joint stiffness inevitably induces an increase in the axial elongation and vice versa. That is, the joint stiffness and the axial elongation cannot be controlled independently, as the number of control inputs is restricted to three.

The orientation $(\alpha, \beta)$ of the robot arm is retrieved from a motion capture system with sub-millimeter accuracy. Proportional valves are deployed to control the pressure in the actuators. A vacuum ejector module is used for the vacuum generation for the end effector.

III. DELTA REPRESENTATION

Directly applying the pressures $p_A, p_B$ and $p_C$ to the system would simultaneously affect the orientation and the joint stiffness of the robot arm. Therefore, we introduce a mapping which allows us to represent a point $(p_{AB}, p_{BC})$ by two variables related to the angular deflection of the arm and a variable connected to the joint stiffness. To this end, we first generalize the concept of pressure difference to the case of three pressures. Based on this, a mapping is derived which decouples the two angular degrees of freedom, $\alpha, \beta$ allowing us to simplify the modeling and control approach. Finally, the proposed mapping is experimentally validated.

A. Pressure Difference

The motivation to rely on pressure differences becomes clear when considering a system with a single degree of freedom with antagonistic actuation (see [9] and [18] for examples). Due to the opposing directions of the forces applied by each actuator, the pressure difference between the two actuators is directly coupled to the angular deflection.

For the case of three independent actuators A, B, and C and corresponding pressures $p_A, p_B$ and $p_C$, we define the pressure differences as

$$\Delta p_{AB} := p_A - p_B, \quad \Delta p_{BC} := p_B - p_C.$$  \hspace{1cm} (1)

Note that this definition is arbitrary as long as each pressure occurs at least once in the equations. The difficulty lies in the determination of the inverse mapping, i.e. the relation...
from $\Delta p_{AB}, \Delta p_{BC}$ to $p_A, p_B, p_C$. The inverse mapping is straightforward for the case of two pressures and presented in [18]. In the following, we present the generalization to the case of three actuators. Only two equations are provided in [1] which contain three unknowns. In order to obtain a unique solution for $p_A, p_B, p_C$, a third variable is required, namely
\[
\bar{p} = \min(p_A, p_B, p_C).
\] (2)

The parameter $\bar{p}$ corresponds to the lower pressure level in all three actuators, similarly used in [9] and [10] to adjust the stiffness of the joint for a single or two degrees of freedom system, respectively. One can show that the inverse mapping, from $\bar{p}, \Delta p_{AB}, \Delta p_{BC}$ to $p_A, p_B, p_C$, is given by
\[
p_A = \max\{\bar{p}, \bar{p} + \Delta p_{AB}, \bar{p} + \Delta p_{AB} + \Delta p_{BC}\}
\] (3)
\[
p_B = \max\{\bar{p}, \bar{p} + \Delta p_{BC}, \bar{p} - \Delta p_{AB}\}
\] (4)
\[
p_C = \max\{\bar{p}, \bar{p} - \Delta p_{BC}, \bar{p} - \Delta p_{AB} - \Delta p_{BC}\}.
\] (5)
The inverse mapping defined by (3)-(5) ensures that $p_i \geq \bar{p}$, $i \in \{A, B, C\}$ at all times. Notice that at least one of these inequality constraints is always active. Furthermore, note that the differences $p_A - \bar{p}$ and $p_B - \bar{p}$ result in $\Delta p_{AB}$ and $\Delta p_{BC}$ as desired, when applying (3)-(5).

### B. Decoupling

The mapping introduced in the previous section allows us to uniquely represent three absolute pressures $p_A, p_B, p_C$ using two variables $\Delta p_{AB}, \Delta p_{BC}$ which are related to an excitation in the $\alpha$-$\beta$-plane and one variable $\bar{p}$ which is related to stiffness. The pressure differences $\Delta p_{AB}, \Delta p_{BC}$ have associated directions of action resulting from the configuration of the actuators. The associated directions of action of $\Delta p_{AB}, \Delta p_{BC}$ can be explicitly computed by introducing a kinematic model of the soft robotic arm. A kinematic relationship between the pressures and their effect on $\alpha, \beta$, assuming small values for $\alpha$ and $\beta$, is introduced in [10], namely
\[
\alpha \propto \frac{\sqrt{3}}{2} p_B - \frac{\sqrt{3}}{2} p_C
\] (6)
\[
\beta \propto -p_A + \frac{1}{2} p_B + \frac{1}{2} p_C.
\] (7)
Combining the definitions in (1) with (6), (7) allows us to define the decoupled pressure differences $\Delta p_{\alpha}$ and $\Delta p_{\beta}$, which are aligned with the orientations $\alpha$ and $\beta$, namely
\[
\begin{bmatrix}
\Delta p_{\alpha} \\
\Delta p_{\beta}
\end{bmatrix} :=
\begin{bmatrix}
0 & \sqrt{3}/2 \\
-1 & -1/2
\end{bmatrix}
\begin{bmatrix}
\Delta p_{AB} \\
\Delta p_{BC}
\end{bmatrix}.
\] (8)

Note that the linear transformation is invertible.

### C. Composition and Experimental Validation

The composition of (3)-(5) and the inverse of (8) allows us to define a bijective mapping, denoted as
\[
(p_A, p_B, p_C) = \xi(\bar{p}, \Delta p_{\alpha}, \Delta p_{\beta}).
\] (9)

A point $(\bar{p}, \Delta p_{\alpha}, \Delta p_{\beta})$ is referred as the Delta Representation of a corresponding point in the absolute pressure space $(p_A, p_B, p_C)$. A change in $\Delta p_{\alpha}$ solely affects the orientation $\alpha$ and analogously for $\Delta p_{\beta}$ and $\beta$, independent of $\bar{p}$. For the purpose of validation, sinusoidal trajectories with respect to $\Delta p_{\alpha}$ and $\Delta p_{\beta}$ are applied. The corresponding pressure setpoint trajectories (for a fixed value of $\bar{p}$) are computed offline using (9) and tracked by three independent pressure controllers. An example for the trajectory in the Delta Representation space and the resulting trajectory in the angle space $(\alpha, \beta)$ is shown in Fig. 3. Note that no angle control is applied. The use of the Delta Representation induces a similarity property between the angle and pressure space. The decoupling characteristics simplify the modeling process as discussed in the next section.

### IV. Modeling

In this section, the modeling and parameter identification of the soft robotic arm are presented. An LPV model is developed, which captures the fundamental behavior of the system. The underlying requirement is to be sufficiently descriptive for controller synthesis, assuming inaccuracies and model uncertainties can be compensated by feedback control and a learning control strategy (see Sec. [7]).

Because of the lightweight structure of the robotic arm, the load mass, $m$, has a significant influence on the dynamics of the system. This becomes particularly important when carrying a load mass in the order of the mass of the movable link during a pick-and-place application. Therefore, the dependency of the load mass is explicitly considered in the modeling process. Similarly, the parameter for the lower pressure bound $\bar{p}$ has a significant influence on the system dynamics due to its strong connection to the joint stiffness. As a consequence of defining the input in the Delta Representation space, the model structure is assumed to be diagonal, namely
\[
\begin{bmatrix}
\alpha(s) \\
\beta(s)
\end{bmatrix} =
\begin{bmatrix}
G_{\alpha}(s, \bar{p}, m) & 0 \\
0 & G_{\beta}(s, \bar{p}, m)
\end{bmatrix}
\begin{bmatrix}
\Delta p_{\alpha}(s) \\
\Delta p_{\beta}(s)
\end{bmatrix},
\] (10)
representing an LPV system with respect to the quasi statically assumed parameters $\bar{p}$ and $m$, where $s$ denotes the Laplace variable. The modeling process can be divided into two steps. First, a gray box model is derived, allowing us to
incorporate first principles knowledge. Secondly, the parameters are estimated using a frequency domain identification procedure.

A. Gray Box Model

We consider the system as two independent (linearized) pendulums. Given the robot configuration as depicted in Fig. 1 the linearized dynamics are given by,

\[ \left( mR_0^2 + M \frac{R_0^2}{4} \right) \ddot{\alpha} + d_\alpha \dot{\alpha} + k_\alpha \alpha = \tau_\alpha, \]  

(11)

and analogously for \( \beta \). The parameter \( R_0 \) represents the radius of the movable link from the pivot point to the load mass, when the soft joint is not extended. The second inertia term in (11) accounts for the inertia of the movable link, where a distance of \( R_0/2 \) is assumed from the pivot point to the center of mass of the movable link without any load mass attached. The mass of the movable part is denoted by \( M \). The stiffness and damping parameters \( k_i, d_i \) are unknown and estimated from experimental data as discussed in the subsequent paragraph. The mass-related parameters are measured with a weighing scale. The driving torque \( \tau_i \) is assumed to be a linear dynamic system in the decoupled pressure difference, namely,

\[ \tau_i(s) = H_i(s, \bar{p}) \Delta p_i(s), \quad i = \alpha, \beta, \]  

(12)

where the order and the parameters of the transfer function are determined from identification experiments. It is assumed that the parameters of \( H_i \), as well as the stiffness and damping coefficients \( k_i, d_i \), solely depend on \( \bar{p} \) and are independent of \( m \). As a consequence, the parameter estimation experiments can be conducted for a fixed load mass \( m \), as its influence can be extrapolated from the first principles model in (11). The system identification experiments only address variations with respect to \( \bar{p} \), which significantly reduces the number of experiments required.

B. Parameter Estimation

In order to estimate the parameters of the differential equations (11) and (12), system identification experiments are conducted. The choice of the excitation signal is simplified as the input of the plant is defined in the Delta Representation space. This allows the excitation signal to attain both positive and negative values. The system is excited with a series of sinusoidal inputs providing a high signal to noise ratio as the entire signal energy is concentrated at a single frequency. For each frequency, the input signal is repeated over ten periods. The first four periods are discarded to minimize the influence of transients. The remaining periods are averaged in order to reduce the variance of the estimate. The magnitude and phase of the output response are estimated using a sinusoidal correlation method, as described in [19]. The experiments are conducted for five different values of \( \bar{p} \) and no load mass attached \( (m = 0) \). The Bode plot of the identified frequency response data and the corresponding fits are shown in Fig. 4. Complex curve fitting as described in [20] is used to fit the parameters of the transfer functions. The best fit for \( G_\alpha \) and \( G_\beta \) is obtained for an order of three. As the order of the equation of motion (11) is two, the order of the driving torque function (12) is consequently given as one. The overall transfer function from the decoupled pressure difference to the angle is given by,

\[ G_i(s, \bar{p}, m) = \frac{\eta_i}{T_i s + 1} \frac{1}{(m + M/4)R_0^2 s^2 + d_\alpha s + k_\alpha}, \]  

(13)

for \( i = \alpha, \beta \). In order to obtain a fully parametric model, polynomials are fitted for the parameters \( \eta_i = \eta_i(\bar{p}), T_i = T_i(\bar{p}), d_i = d_i(\bar{p}), k_i = k_i(\bar{p}) \) for \( i = \alpha, \beta \) as a function of \( \bar{p} \). The corresponding fits are shown in Fig. 5. The result is a fully parametric LPV model with respect to the parameters \( \bar{p} \) and \( m \).

V. CONTROL

In this section, the control architecture of the system is discussed. First, the design of a gain-scheduled feedback controller is presented, based on the LPV model introduced
in the previous section. In the second part, an ILC strategy is presented which can compensate for repetitive errors enabling accurate tracking of aggressive trajectories. The tracking performance of both feedback controller and ILC is evaluated with and without a load mass attached to the robot arm to validate its generalization to different load masses.

A cascaded control architecture is employed as shown in Fig. 6. The outputs of the angle controller are the setpoints $\Delta p_{\alpha,SP}$, $\Delta p_{\beta,SP}$. Consequently, the controller has no influence on the compliance of the system allowing us to consider stiffness and motion control to be independent. The parameter $\beta$ represents an additional degree of freedom in the control system and can be specified by the user. The setpoints in the Delta Representation are transferred to the absolute pressure space by using (9). The actuator pressures $p_A$, $p_B$, $p_C$ are controlled by three independent Proportional–Integral–Derivative (PID) controllers in inner control loops.

### A. Feedback Control

The feedback control structure is based on the decoupled model presented in [10]. The following feedback controller is proposed, for each degree of freedom,

$$C_i(s, \bar{p}, m) = \kappa_i \frac{(m + M/4)R_0^2s^2 + d_is + k_i}{s}, \quad i = \alpha, \beta,$$

which represents a linear gain-scheduled controller, parametrized by $m$ and $\bar{p}$. Assuming that $m$ and $\bar{p}$ are known, the controller $C_i(s, \bar{p}, m)$ asymptotically stabilizes the closed loop system with infinite gain margin for $\kappa_i > 0$. Note that this stability guarantee only holds for a neighborhood of the origin $(\alpha, \beta) = (0, 0)$ due to the linear nature of the model. Furthermore, the guarantee is only valid assuming the parameters $m$ and $\bar{p}$ to be constant or changing sufficiently slowly with respect to time [21, p. 48]. A feedforward component is added, which compensates for gravitational effects acting on $\beta$ and not covered in [11], namely,

$$\Delta p_{\beta,ff} = \frac{1}{\eta_\beta}(MgR_0^2 + mgR_0) \cos(\beta_{SP}),$$

where $\eta_\beta$ represents the static pressure to torque gain from [12] and [13], respectively.

The tracking performance of the feedback controller with and without a load mass attached is shown in Fig. 7. Notice, the similarity in terms of tracking performance, which implies that the effect of the load mass is well captured by the first principles model and can be compensated by the pole-zero cancellation structure of the controller. The main task of the feedback controller is to ensure asymptotic stability over the entire domain of $\bar{p}$ and $m$, to provide steady state accuracy and to reject non-repetitive disturbances. However, for aggressive maneuvers oscillations are present and the overshoot is too high in order to reliably realize a pick-and-place application. As the system is characterized by a high repeatability, this effect can be compensated by the application of an ILC scheme as discussed in the following paragraph.

### B. Iterative Learning Control

ILC allows for accurate reference tracking in repetitive tasks [22], as often encountered in pick-and-place applications. The basic idea of ILC is to adapt a feedforward/reference signal based on the error information from the previous iterations. In general, ILC can be deployed in serial or in parallel with a feedback controller. In the following, a norm-optimal iterative learning controller in a serial architecture is employed [23]. A serial architecture simplifies the design process of the ILC as it allows us to assume the dynamics to be parameter-independent, given the
The vector control structure proposed above. In particular, the closed loop dynamics are Independent of the parameter due to pole-zero cancellation in the open-loop system. Note that the feedback controller structure cannot fully compensate the influence of \( \bar{p} \), in particular the driving torque \( -N_1 \), in particular, the driving torque \( -N_1 \), which corresponds to a discrete-time first-order derivative operator,\( \frac{D}{T_s} \), representing the identity matrix, \( T_s \) the sampling time, and \( \otimes \) the Kronecker product and
\[
\hat{D} = \begin{bmatrix}
-1 & 1 & \cdots & 0 & 0 \\
0 & -1 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & -1 & 1 \\
0 & 0 & \cdots & 0 & 0
\end{bmatrix} \in \mathbb{R}^{N \times N}.
\]

The terms in the cost function can be interpreted as follows. The first term penalizes the error in the next iteration, the second term penalizes changes in the reference correction signal from iteration to iteration and the last term allows us to restrict fast changes in the correction signal. As no constraints with respect to the correction signal are considered, the optimal solution can be computed in closed form,
\[
u^{j+1} = \arg \min_{\nu^j} \{ J^{j+1}(\nu^{j+1}) \} = Q \nu^j + L e^j,
\]
with
\[
Q = (P^T W_e P + W_{\Delta u} + D^T W_{\Delta u} D)^{-1} (P^T W_e P + W_{\Delta u})
\]
\[
L = (P^T W_e P + W_{\Delta u} + D^T W_{\Delta u} D)^{-1} P^T W_e.
\]

The experimental results when applying the ILC scheme are shown in Fig. 8 with and without a mass attached. Note that the reference trajectories slightly differ with respect to the two cases considered. The proposed ILC approach allows for accurate reference tracking of aggressive trajectories.
independent of the attached load mass, while using the same tuning matrices. For instance, with a mass attached, the root-mean-square error in $\alpha$ can be reduced from 3.3° in the first iteration (no learning) to 0.32° in iteration 24, while the maximum norm of the error can be reduced from 18.9° to 1.4°. Similar improvements are obtained for the case with no mass attached, illustrating the advantage of the serial architecture of the ILC.

VI. APPLICATION

In this section, the pick-and-place application is described. First, the procedure to axially approach and pick an object by means of the axial compliance of the soft joint is presented. Subsequently, the experimental results and the procedure for the realization of the pick-and-place operation are discussed.

A. Picking an Object

In general, vacuum grippers are not suitable when the range of motion of the robot arm is restricted to a spherical cap as the suction cup inevitably collides with the object when approaching sideways. Furthermore, it is impossible to suck in the object with the vacuum gripper even if the distance between the object and the suction cup is in the order of a millimeter, due to the limited air flow. In order to pick an object in a robust and reliable way with a vacuum gripper, it is crucial to axially approach and adhere the object. As the system is equipped with a soft joint (see Sec. II) with certain axial compliance, objects can be approached in the axial direction. To control the axial elongation of the soft joint, the lower pressure bound $\bar{p}$ is increased (see Fig. 10 (bottom)). However, for rapid increases in $\bar{p}$ this causes an error with respect to the constant angle reference which cannot be compensated by the feedback controller. Note that the Delta Representation solely ensures a decoupling between $\alpha$, $\beta$, but not their invariance with respect to $\bar{p}$. In order to provide accurate tracking of the constant reference, when simultaneously approaching the object, the same ILC strategy is applied when picking an object as introduced in the previous section. Note that the scope of the underlying model is restricted to quasi static changes with respect to $\bar{p}$. However, the model is sufficiently descriptive for the ILC synthesis. The ability of the system to track constant references while simultaneously moving in the axial direction using ILC is shown in Fig. 9.

B. Pick-and-Place

The pick-and-place application consists of three phases, namely (I) picking an object, (II) carrying a load from the initial to the terminal position and (III) returning to the initial position after depositing the object into a box. The full duration of a pick-and-place period is 2.78 sec for a reference change of approximately 60°. The reference change occurs within 0.6 sec in phase (II) and within 0.3 sec in phase (III). An ejection impulse is applied between phases (II) and (III) when depositing an object to ensure rapid purging of the vacuum by the active pressurization of the suction cup (see phase (E) in Fig. 10).

In order to track the pick-and-place trajectories accurately, the ILC strategy from the previous section is applied. This, however, requires the ILC to be initialized with a warm start to ensure that the deposition of the object does not occur in an uncontrolled way due to the large overshoots when no learning is applied in aggressive maneuvers (see Fig. 8). To this end, all three phases of the pick-and-place application are first trained independently. The experimental results of the independently trained task are depicted in Fig. 9 for phase (I), Fig. 8 (bottom) for phase (II) and Fig. 8 (top) for the phase (III). The learned correction signals are truncated appropriately and concatenated resulting in the warm start correction signal. Subsequently, the ILC for the pick-and-place application is trained for the entire pick-and-place operation jointly, initialized with the warm start. The
mass parameter for the underlying feedback control loop is changed continuously between the different phases. Fig. 10 shows the tracking performance during the pick-and-place application when applying the warm start and after the ILC scheme applied to the entire application has converged.

The implemented ILC approach allows for accurate and fast pick-and-place tasks. Note the high accuracy when depositing the mass, which is attributable to the non-causal nature of the ILC scheme. The interested reader is referred to Fig. 11 and to the video attachment to gain a visual impression of the system during operation and the application performed [https://youtu.be/00V1Z-R81sg]. After convergence of the ILC, the pick-and-place application works reliably, which is demonstrated in the video attachment with 50 out of 50 consecutive successful trials.

VII. CONCLUSION

A pick-and-place application is successfully implemented on a soft robotic arm. The reliability and high payload to weight ratio demonstrates the system’s ability to be deployed in a real-world application. It is shown that one translational/stiffness and two rotational degrees of freedom can be controlled simultaneously using a soft joint. A mapping based on pressure differences and the antagonistic actuation principle is introduced, allowing us to significantly reduce the complexity of the developed LPV model due to its decoupling property. Based on this model, a gain-scheduled feedback controller is designed, which shows comparable tracking performance irrespective of the load mass attached.

An ILC scheme enables accurate tracking during aggressive maneuvers allowing the realization of the application proposed.

Currently, it is assumed that the mass is known to the feedback controller. Future work will address the estimation of the load mass online based on the model presented, the consideration of variable stiffness along the trajectories and the manipulation of different types of objects.

ACKNOWLEDGMENT

The authors would like to thank B. Walser, W. Bachmann, H. Yaohui, H. Hanimann and the Niederberger-Kobold Foundation for their contributions to this work.

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