Passivity Based Iterative Learning of Admittance-Coupled Dynamic Movement Primitives for Interaction with Changing Environments

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***Abstract*— Encoding desired motions into dynamic movement primitives (DMPs) is a common way for generating compact task representations that are able to handle sensor-based goal adaptations. At the same time, a robot should not only express adaptive motion capabilities at planning level, but use also contact wrench feedback in the adaptation and learning process of the DMP. Despite first approaches exist in this direction, no fully integrated approach has been proposed so far. In this paper, we introduce a new class of admittance-coupled DMPs that addresses environmental changes by including contact wrench feedback dynamics into the DMP formalism. Moreover, a novel iterative learning approach is devised that is based on monitoring the overall system passivity analysis in terms of reference power tracking. Simulations and experimental results with the Kuka LWR robot maintaining a non-rigid contact with the environment (wiping a surface) are shown for supporting the validity of our approach.**

I. INTRODUCTION

Learning by demonstration (LbD) is a standard way for enabling robots to perform desired tasks. This can be done by encoding the desired motion through Dynamic Movement Primitives (DMPs). However, motion alone obviously does not contain all relevant information in contact or even complex manipulation tasks. The desired contact wrenches play an equally important role. Furthermore, changes in the environment such as object locations may cause the encoded motion to become invalid. However, the desired wrenches may remain valid, in particular if the objects to be manipulated are still the same ones.

One way to achieve such a behavior would be to follow the trajectory and track forces e.g. via the unified force/impedance control from [1]. However, this would put the entire burden of adaptation on the controls level, with the planing (trajectory) level ignoring any changes in the actual task. This is why in our previous work [2], we introduced a framework in which the impedance control set-point is generated by a DMP and modified by an external admittance controller. This scheme could then be combined with the unified force / impedance controller.

In this paper, we go a significant step further. In addition to the standard encoding of desired trajectory dynamics into a DMP, the introduced admittance dynamics are directly coupled into the DMP framework, which aims to include force feedback on trajectory level similar to our previous approach [3]. With the help of this algorithm we can respect now both, the encoded trajectory and the desired wrench profiles at planning level. This leads us to the concept of reference power. As we will argue throughout the paper the

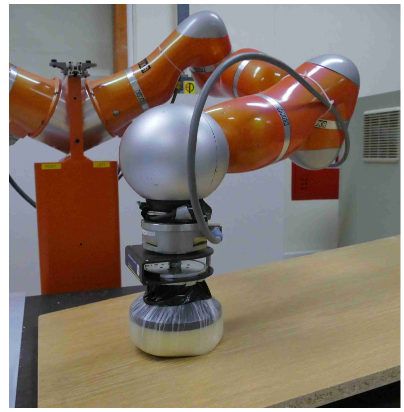

Fig. 1: Experimental setup for the evaluation. Non-rigid contact, i. e., wiping of surface was chosen as the use-case scenario. The robot adapts its motion based on the observed passivity.

force feedback helps us to adapt the desired trajectory such that this task can be successfully executed even though environment changes may have occurred. In case it is permanent, the effect of the coupling term needs to be made permanent, i.e. it has to be learned. We tackle this task with the help of iterative learning control (ILC). Specifically, we update the DMP goal after an iteration in case the coupling term is activated, which essentially means that the desired wrench was not well tracked anymore. To perform a meaningful update, a passivity-based stability criterion observing the deviation from the reference power is used to drive the system back towards more stable regimes. The overall behavior of the system shows promising experimental results. As is shown in the experimental part, our algorithm reduces the force deviation that may occur due to environmental changes, while stabilizing the system by decreasing the reference power error. Note that beyond the stability and passivity analysis we provide for the admittance-based coupled DMP, a full stability regain analysis of the proposed learning process is left for future work. Lastly, we would like to mention that the developed scheme may also be used for robots that only provide position control interfacing with underlying torque or current loops.

A. *Related work*

Several topics of research are combined in the proposed approach. One is *adaptive learning by demonstration*. In this paper we rely on the DMP framework, which is common in LbD approaches. The DMP framework was thoroughly explored for different learning and adaptation situations. For example, for different kinds of adaptation [4], with reinforcement learning [5], [6], for generalization of motion [7], for adaptation of motion based on force feedback [3],

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[8], etc. We use the coupled DMPs from [3], which couple force feedback to the position and velocity of the DMP. We further extend this by combining it with the approach in [4] to smoothly change the goal, thus facilitating the adaptation of a complete admittance controller within the DMP structure.

Another topic is *learning*, which was also thoroughly explored in robotics, e. g., see [6], [9], [10]. Most related to our work is the learning of DMP trajectories based on force feedback. Examples of such are in, for example [11], [12] or [13]. In the latter the authors combined coupled DMP adaptation with no-reset iterative learning control (ILC), however they used simple force feedback. The approach is somewhat similar to the one proposed in this paper, where we use the passivity observer feedback signal as the criterion for learning. ILC uses the information from a previous execution to update the current execution, and has been extensively applied in robotics [14], including the no-reset ILC [15].

A major topic of this paper is *passivity*. As discussed in the introduction, it essentially defines the system property of not producing more energy than it receives. While passivity has found its way into stability analyses much earlier in the field of network analysis [16], one of its first application in robotics has been in adaptively controlling manipulators [17]. When it comes to interaction control, and specially for impedance control [18], passivity has been proven in regulation (i.e. *compliance* control) [19]. Nevertheless, impedance control for motion tracking is proven not to be a passive behavior [20]. In tele-operation applications the concept of reference energy has been used [21]. As trajectory tracking in our paper is implemented via DMPs, its dynamics needs to be taken into account for overall passivity analysis, and to the best of our knowledge, this has not been done before.

B. Contributions

The contributions of the present work are as follows.

1) A novel admittance based dynamics embedding, extending the coupled DMP framework introduced in [3] to *Admittance-coupled DMPs*,
2) a passivity analysis of the impedance controlled robot driven by the Admittance coupled DMP,
3) DMP goal learning based on reference power error monitoring.

The remainder of the paper is organized as follows. Section II provides relevant background, including the basics of DMPs and the evolution to Admittance-coupled DMPs. This is followed by the passivity analysis of the system in Section III in which a passivity criterion is defined. The learning approach based on current-iteration ILC uses this criterion as a feedback learning signal in Section IV. Experimental evaluation in simulation and on the real robot is discussed in Section V. The overall system applicability, structure and behavior are discussed. Finally, conclusions are drawn in Section VI.

II. Background

A. Cartesian Impedance Controlled Rigid-body Robot

A Cartesian impedance controlled rigid-body manipulator with n degrees of freedom in contact with the environment and with the desired inertia identical to the robots inertia [20] is describable by the closed-loop dynamics

$$\boldsymbol{M}_C(\boldsymbol{q})\ddot{\tilde{\boldsymbol{x}}} + \left(\boldsymbol{C}_C(\boldsymbol{q},\dot{\boldsymbol{q}}) + \boldsymbol{D}_x\right)\dot{\tilde{\boldsymbol{x}}} + \boldsymbol{K}_x\tilde{\boldsymbol{x}} = \boldsymbol{F}_{\text{ext}} \tag{1}$$
$$\tilde{\boldsymbol{x}} = \boldsymbol{x} - \boldsymbol{x}_d, \tag{2}$$

where $\boldsymbol{q} \in \mathbb{R}^n$ denotes the link position and $\boldsymbol{x} \in \mathbb{R}^6$ and $\boldsymbol{x}_d \in \mathbb{R}^6$ respectively denote the actual and desired pose in Cartesian space. As will be seen in the following, $\boldsymbol{x}_d$ is the output of the coupled DMP. Moreover, $\boldsymbol{F}_{\text{ext}} \in \mathbb{R}^6$ denotes the external wrench applied to the robot, and $\boldsymbol{M}_C(\boldsymbol{q}) \in \mathbb{R}^{6\times6}$ and $\boldsymbol{C}_C(\boldsymbol{q},\dot{\boldsymbol{q}}) \in \mathbb{R}^{6\times6}$ are respectively the robot inertia matrix and Coriolis and centrifugal matrix in Cartesian space. Finally, $\boldsymbol{K}_x \in \mathbb{R}^{6\times6}$ and $\boldsymbol{D}_x \in \mathbb{R}^{6\times6}$ are the desired stiffness, and damping matrices.

B. Admittance-coupled Dynamic Movement Primitives

Our work is based on the periodic dynamic movement primitives framework [22]. The original DMP formulation is given with

$$\tau\dot{\boldsymbol{z}}_{d,0} = \alpha_z\left(\beta_z\left(\boldsymbol{g} - \boldsymbol{x}_{d,0}\right) - \boldsymbol{z}_{d,0}\right) + \boldsymbol{f}_c(\phi), \tag{3}$$
$$\tau\dot{\boldsymbol{x}}_{d,0} = \boldsymbol{z}_{d,0}, \tag{4}$$

where $\tau = 1/\omega$ defines the frequency of the periodic movement[1] and α_z and β_z are positive constants. The output of the DMP is $\boldsymbol{x}_{d,0}$, with $\boldsymbol{g}$ being the anchor of oscillations and $\boldsymbol{f}_c(\phi)$ denotes the periodic forcing term. For an in-depth explanation of DMPs see [22].

In this paper we use coupled DMPs [3], which include force feedback within the DMP formulation, coupled to the velocity of the DMP. Therefore, no additional force controllers are needed. However, the velocity resolved admittance control approach defines the position output $\boldsymbol{x}_a$ as $\dot{\boldsymbol{x}}_a = \boldsymbol{D}_c\left(\boldsymbol{F}_d + \boldsymbol{F}_{\text{ext}}\right)$, where $\boldsymbol{F}_d \in \mathbb{R}^6$ is the desired wrench and $\boldsymbol{D}_c \in \mathbb{R}^{6\times6}$ is a symmetric positive-definite matrix. To account also for the integral part of the admittance controller, we add the coupling term also to the goal $\boldsymbol{g}$, similar to the approach for changing DMPs in [4]. The final formulation of the coupled DMP thus becomes

$$\tau\dot{\boldsymbol{z}}_d = \alpha_z\left(\beta_z\left(\boldsymbol{g} + \boldsymbol{c} - \boldsymbol{x}_d\right) - \boldsymbol{z}_d\right) + \boldsymbol{f}_c(\phi) \tag{5}$$
$$\tau\dot{\boldsymbol{x}}_d = \boldsymbol{z}_d + \tau\dot{\boldsymbol{c}} \tag{6}$$
$$\dot{\boldsymbol{c}} = \boldsymbol{D}_c\left(\boldsymbol{F}_d + \boldsymbol{F}_{\text{ext}}\right). \tag{7}$$

Here $\dot{\boldsymbol{c}}$ is the coupling term, which changes the velocity and consequently the position output of the DMP. The initial wiping movement was demonstrated to the system using LbD method as presented in [23].

III. Passivity Analysis

As an intuitive way to investigate stability, passivity analysis is applied to the overall system of impedance-controlled manipulator in contact with environment. Afterwards, the dynamics of coupled DMP is taken into account and finally a virtual tank, based on a passivity observer (PO) is designed to ensure the overall system passivity.

A system with state $\boldsymbol{\chi} \in \mathbb{R}^m$ and the state space model

$$\dot{\boldsymbol{\chi}} = f(\boldsymbol{\chi}, \boldsymbol{u}) \tag{8}$$
$$\boldsymbol{y} = h(\boldsymbol{\chi}, \boldsymbol{u}), \tag{9}$$

[1]We chose the notation with τ for clarity throughout the passivity analysis.

where $\boldsymbol{u}, \boldsymbol{y}$ with the same dimension, are respectively the input and output, is said to be passive if there exists a function (namely *Storage function*) $S : \mathbb{R}^m \rightarrow \mathbb{R}_+$ such that

$$S(\boldsymbol{\chi}(\sigma)) - S(\boldsymbol{\chi}_0) \leq \int_0^\sigma \boldsymbol{u}^T(t)\boldsymbol{y}(t)dt \tag{10}$$

for all inputs $\boldsymbol{u} : [0, \sigma] \rightarrow \mathbb{R}^l$, initial states $\boldsymbol{\chi}_0 \in \mathbb{R}^m$ and $\sigma > 0$ [24]. Consequently a system is passive w.r.t. $\langle \boldsymbol{u}, \boldsymbol{y} \rangle$ if

$$\dot{S} \leq \boldsymbol{u}^T\boldsymbol{y}, \quad \forall(\boldsymbol{\chi}, \boldsymbol{u}), \tag{11}$$

where $\boldsymbol{u}^T\boldsymbol{y}$ is the input power to system (8)-(9).

A. Passivity of Cartesian impedance controlled robot in contact with passive environment

Considering a passive environment w.r.t. the pair $\langle \dot{\boldsymbol{x}}, -\boldsymbol{F}_{\text{ext}} \rangle$, a storage function S_{env} can be assumed such that

$$\dot{S}_{\text{env}} \leq -\dot{\boldsymbol{x}}^T\boldsymbol{F}_{\text{ext}}. \tag{12}$$

Moreover, for the Cartesian impedance controlled rigid-body manipulator with closed loop dynamics (1), a storage function S_m can be defined as

$$S_m = \frac{1}{2}\tilde{\boldsymbol{x}}^T\boldsymbol{K}_x\tilde{\boldsymbol{x}} + \frac{1}{2}\dot{\tilde{\boldsymbol{x}}}^T\boldsymbol{M}_C(\boldsymbol{q})\dot{\tilde{\boldsymbol{x}}}. \tag{13}$$

It is straight-forward[2] to see that

$$\begin{aligned}\dot{S}_m &= \dot{\tilde{\boldsymbol{x}}}^T\boldsymbol{F}_{\text{ext}} - \underbrace{\dot{\tilde{\boldsymbol{x}}}^T\boldsymbol{D}_x\dot{\tilde{\boldsymbol{x}}}}_{\geq 0} \\ &\leq \dot{\boldsymbol{x}}^T\boldsymbol{F}_{\text{ext}} - \dot{\boldsymbol{x}}_d^T\boldsymbol{F}_{\text{ext}}.\end{aligned} \tag{14}$$

Now, by introducing S_{sys} as the storage function for the supersystem of controlled manipulator and environment such that

$$S_{\text{sys}} = S_m + S_{\text{env}}, \tag{15}$$

and considering (12) and (14), it can be seen that

$$\begin{aligned}\dot{S}_{\text{sys}} &= \dot{S}_m + \dot{S}_{\text{env}} \\ &\leq -\dot{\boldsymbol{x}}^T\boldsymbol{F}_{\text{ext}} + \dot{\boldsymbol{x}}^T\boldsymbol{F}_{\text{ext}} - \dot{\boldsymbol{x}}_d^T\boldsymbol{F}_{\text{ext}} \\ \Longrightarrow \dot{S}_{\text{sys}} &\leq -\dot{\boldsymbol{x}}_d^T\boldsymbol{F}_{\text{ext}}.\end{aligned} \tag{16}$$

Thus, this system is passive w.r.t. the pair $\langle \dot{\boldsymbol{x}}_d, -\boldsymbol{F}_{\text{ext}} \rangle$, and the input power is

$$P_{\text{in}} = -\dot{\boldsymbol{x}}_d^T\boldsymbol{F}_{\text{ext}}. \tag{17}$$

B. Passivity of the coupled DMP

Re-writing the original DMP (3)-(4) and coupled DMP dynamics (5)-(6) results in

$$\tau^2\ddot{\boldsymbol{x}}_{d,0} + \alpha_z\tau\dot{\boldsymbol{x}}_{d,0} + \alpha_z\beta_z\boldsymbol{x}_{d,0} = \alpha_z\beta_z\boldsymbol{g} + \boldsymbol{f}_c(\phi) \tag{18}$$

$$\begin{aligned}\tau^2\ddot{\boldsymbol{x}}_d + \alpha_z\tau\dot{\boldsymbol{x}}_d + \alpha_z\beta_z\boldsymbol{x}_d =& \alpha_z\beta_z\boldsymbol{g} + \boldsymbol{f}_c(\phi) + \tau^2\ddot{\boldsymbol{c}} \\ &+ \alpha_z\tau\dot{\boldsymbol{c}} + \alpha_z\beta_z\boldsymbol{c}.\end{aligned} \tag{19}$$

Subtracting (18) from (19), and defining $\tilde{\boldsymbol{x}}_d := \boldsymbol{x}_d - \boldsymbol{x}_{d,0}$ it can be seen that

$$\tau^2\ddot{\tilde{\boldsymbol{x}}}_d + \alpha_z\tau\dot{\tilde{\boldsymbol{x}}}_d + \alpha_z\beta_z\tilde{\boldsymbol{x}}_d = \tau^2\ddot{\boldsymbol{c}} + \alpha_z\tau\dot{\boldsymbol{c}} + \alpha_z\beta_z\boldsymbol{c}. \tag{20}$$

[2]For the detailed-proof please refer to [2].

Applying Laplace transformation on (20) results in

$$\begin{aligned}(\tau^2 s^2 + \alpha_z\tau s + \alpha_z\beta_z)\tilde{\mathcal{X}}_d &= (\tau^2 s^2 + \alpha_z\tau s + \alpha_z\beta_z)\mathcal{C} \\ \Longrightarrow \tilde{\mathcal{X}}_d &= \mathcal{C}\end{aligned} \tag{21}$$

where $\tilde{\mathcal{X}}_d$ and $\mathcal{C}$ are $\tilde{\boldsymbol{x}}_d$ and $\boldsymbol{c}$ in Laplace domain. Transforming (21) back to the time domain, it can be deduced that

$$\boldsymbol{x}_d - \boldsymbol{x}_{d,0} = \boldsymbol{c}. \tag{22}$$

Now, inserting (22) into (16), the system of Cartesian impedance controlled manipulator in contact with environment can be proven to be passive w.r.t. two pairs of $\langle \dot{\boldsymbol{x}}_{d,0}, -\boldsymbol{F}_{\text{ext}} \rangle$ and $\langle \dot{\boldsymbol{c}}, -\boldsymbol{F}_{\text{ext}} \rangle$, i.e.

$$\dot{S}_{\text{sys}} \leq -\dot{\boldsymbol{x}}_{d,0}^T\boldsymbol{F}_{\text{ext}} - \dot{\boldsymbol{c}}^T\boldsymbol{F}_{\text{ext}}. \tag{23}$$

Considering (7), the associated power to the port $\langle \dot{\boldsymbol{c}}, -\boldsymbol{F}_{\text{ext}} \rangle$ can be written as

$$\begin{aligned}-\dot{\boldsymbol{c}}^T\boldsymbol{F}_{\text{ext}} &= -(\boldsymbol{F}_d + \boldsymbol{F}_{\text{ext}})^T\boldsymbol{D}_c\boldsymbol{F}_{\text{ext}} \\ &= -\underbrace{(\boldsymbol{F}_d + \boldsymbol{F}_{\text{ext}})^T\boldsymbol{D}_c(\boldsymbol{F}_d + \boldsymbol{F}_{\text{ext}})}_{\geq 0} \\ &\quad + \underbrace{(\boldsymbol{F}_d + \boldsymbol{F}_{\text{ext}})^T\boldsymbol{D}_c}_{\dot{\boldsymbol{c}}^T}\boldsymbol{F}_d \\ &\leq \dot{\boldsymbol{c}}^T\boldsymbol{F}_d,\end{aligned} \tag{24}$$

which shows that passivity w.r.t. the pair $\langle \dot{\boldsymbol{c}}, \boldsymbol{F}_d \rangle$ results in[3] the passivity w.r.t. the pair $\langle \dot{\boldsymbol{c}}, -\boldsymbol{F}_{\text{ext}} \rangle$. Inserting (24) into (23) we have

$$\dot{S}_{\text{sys}} \leq \dot{\boldsymbol{c}}^T\boldsymbol{F}_d - \dot{\boldsymbol{x}}_{d,0}^T\boldsymbol{F}_{\text{ext}}. \tag{25}$$

As a result, the input power considered for the passivity analysis of the overall system of the coupled DMP and Cartesian impedance controlled robot in interaction with a passive environment is defined as

$$P_{\text{in}} = \dot{\boldsymbol{c}}^T\boldsymbol{F}_d - \dot{\boldsymbol{x}}_{d,0}^T\boldsymbol{F}_{\text{ext}}. \tag{26}$$

C. Passivity observer based on reference power trajectory

As mentioned before, the coupled DMP (5)-(7) assigns the desired pose $\boldsymbol{x}_d$ for the impedance controller based on the original desired pose $\boldsymbol{x}_{d,0}$ together with desired and sensed wrenches $\boldsymbol{F}_d$ and $\boldsymbol{F}_{\text{ext}}$. In the ideal case, when the desired wrench profile matches with the real wrench applied by the robot to the environment, (i.e. $\boldsymbol{F}_d = -\boldsymbol{F}_{\text{ext}}$), the coupling term is zero and the desired trajectory reduces to the original $\boldsymbol{x}_{d,0}$, see (7). In this case, according to (26), the input power to the system in the ideal case is

$$P_{\text{in}}^\dagger = \dot{\boldsymbol{x}}_{d,0}^T\boldsymbol{F}_d. \tag{27}$$

Considering $P_{\text{in}}^\dagger$ as the desired power profile to the main system, a passive reference system can be assumed with a storage function $S^\dagger$ that provides the main system with the required power $P_{\text{in}}^\dagger$. Thus, the reference system can be

[3]In fact, the coupling signal has acted like a damping system with dissipation power $(\boldsymbol{F}_d + \boldsymbol{F}_{\text{ext}})^T\boldsymbol{D}_c(\boldsymbol{F}_d + \boldsymbol{F}_{\text{ext}})$.

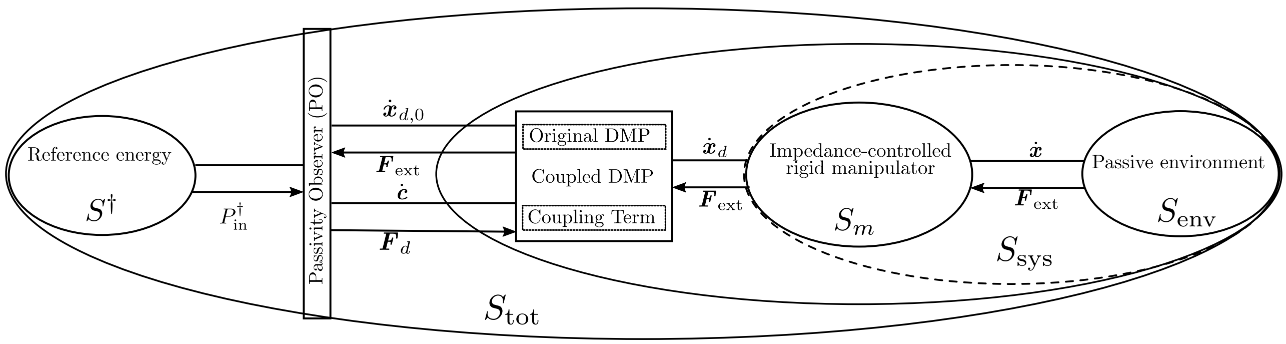

Fig. 2: Depicted overall system consisting of impedance controlled robot in interaction with a passive environment, coupled DMP that provides the impedance control with the desired pose, reference energy provider and passivity observer. Passive subsystems with their respective storage functions are depicted by ellipsoids.

assumed to be passive w.r.t. the same power but with negative sign:

$$\dot{S}^\dagger \leq -P_{\text{in}}^\dagger. \tag{28}$$

Now, based on (25), (26) and (28), an overall system with the storage function S_{tot} can be considered such that

$$S_{\text{tot}} = S_{\text{sys}} + S^\dagger \tag{29}$$

$$\dot{S}_{\text{tot}} \leq \underbrace{P_{\text{in}} - P_{\text{in}}^\dagger}_{P_{\text{acv}}}. \tag{30}$$

Considering this overall system, by ensuring $\dot{S}_{\text{tot}} \leq 0$, it can be deduced that the overall passivity holds when there is no other input port. Thus, based on this criterion, a passivity observer (PO) can be designed such that

$$\begin{cases} \text{Passive} & P_{\text{acv}} \leq 0 \\ \text{Non-passive} & P_{\text{acv}} > 0, \end{cases} \tag{31}$$

where

$$P_{\text{acv}} = P_{\text{in}} - P_{\text{in}}^\dagger \tag{32}$$

$$= \dot{\boldsymbol{c}}^T \boldsymbol{F}_d - \dot{\boldsymbol{x}}_{d,0}^T \boldsymbol{F}_{\text{ext}} - \dot{\boldsymbol{x}}_{d,0}^T \boldsymbol{F}_d. \tag{33}$$

Fig. 2 provides a schematic view of the overall system and its subsystems. In the following, this criterion will be used to adapt the trajectories.

IV. Updating Trajectories

In this paper we use Iterative Learning Control (ILC) to learn the new goal and effectively adapt the motion of the robot solely with the help of the passivity observer (31).

In general, ILC updates the performance in the next repetition of the same task based on the considered feedback. However, in our case we do not use simple, direct feedback of position or force. In fact, the power signal estimated by the passivity observer is incorporated. Specifically, we use ILC to update the DMP goal $\boldsymbol{g}$ in (5) after every repetition of the periodic task by

$$\boldsymbol{g}_{j+1}(l) = \boldsymbol{g}_j(l) + \boldsymbol{K}\boldsymbol{P}_{\text{acv},j}(l), \tag{34}$$

where $\boldsymbol{g}$ is the goal of the DMP, l denotes the l-th time sample, j the iteration of the learning and $\boldsymbol{K}$ a positive diagonal passivity feedback gain. $\boldsymbol{P}_{\text{acv},j}(l)$ denotes the power projected in the respective motion directions, which is obtained from

$$\boldsymbol{P}_{\text{acv},j}(l) = \dot{\boldsymbol{c}}_j \circ \boldsymbol{F}_{d,j} - \dot{\boldsymbol{x}}_{d,0} \circ \boldsymbol{F}_{\text{ext},j} - \dot{\boldsymbol{x}}_{d,0} \circ \boldsymbol{F}_{d,j}, \tag{35}$$

where $\circ$ denotes the Hadamard product. For clarity the desired wrench profile and consequently the trajectory update is done only in a single direction in the following experiments. Essentially this means that $\boldsymbol{g}$, $\boldsymbol{K}$ iand $\boldsymbol{P}_{\text{acv}}$ in (34) become scalar, and $\boldsymbol{P}_{\text{acv}}$ can have the same formulation as P_{acv} taken from (31).

V. Experimental Validation

The proposed learning setup was tested in simulation and on a real system. The task was to adapt and learn the environmental changes upon the passivity observer signal.

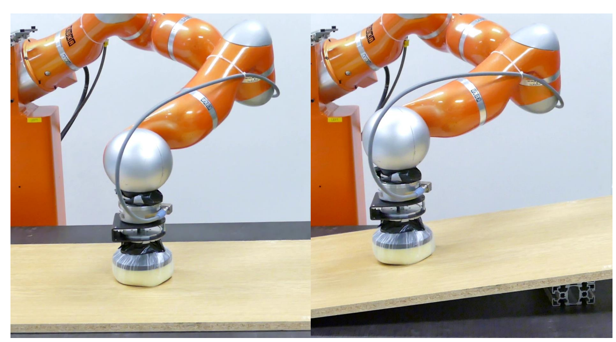

Fig. 3: Execution of the demonstrated trajectory (Left), learning of the changed environment (Right).

A. Simulation results

We first tested the proposed method in simulation. The task was to adapt and learn the motion of the robot in order to maintain a constant contact force with a changing environment mimicking a robot polishing a surface on a slope. Force feedback was realized with the proposed DMP coupling framework. In simulation, $\boldsymbol{F}_{\text{ext}}$ coming from the environment was altered sinusoidally.

Fig. 4 depicts the simulation results, where the dashed black line corresponds to the starting point of the learning. Each oscillation represents one iteration. It can be seen that after a couple of iterations the system learns the goal, while the force error and thus the coupling term of the DMP decay.

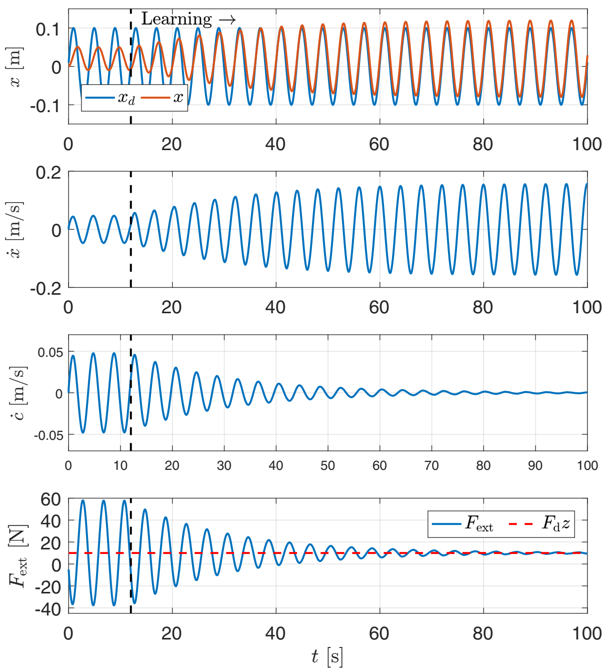

Fig. 4: The first graph shows a simulated DMP and reference positions. The second and third graphs correspond to the DMP and coupling term velocities, as for the fourth graph the simulated environmental forces are show. Vertical black dashed line depicts the start of learning.

The system passivity is monitored by the passivity observer. Its output (Fig. 5 graph 1) is used as input for the DMP goal learning. In Fig. 5, it can be observed that P_{acv} decreases gradually when the DMP trajectory is adapted due to a changing environment. One goal of the learning is to bring P_{acv} approximately to 0, which means that the input power to the system P_{in} matches the reference power $P_{\text{in}}^{\dagger}$.

B. Results on a real system

The experiment was performed with an impedance controlled 7 DOF Kuka LWR robot. The real-world challenge was to learn a wiping trajectory, based upon observing the passivity of the system and maintain the desired normal force $F_d = 10$ N to the environment. Forces acting on the robot were measured at the wrist of the robot with an ATI force-torque sensor, thus providing more accurate Cartesian force/torque reading compared to the LWR integrated joint torque sensors. For clarity the experiment was divided into four sections (*Sec.*) depicted in Figs. 6 and 7, as well as in the accompanying video. First the desired wiping motion was demonstrated to the robot as presented in [12] and encoded with periodic DMPs. Upon execution, force control was realized with a DMP coupling term according to (5)-(7).

In *Sec.1* of the experiment the demonstrated movement is executed with no change in the environment, see Fig. 3 (left). The reference force is tracked (Fig. 7 graph 2) and the passivity is preserved.

Changes in the environment are presented in the form of lifting one side of the table, depicted in experiment *Sec.2* and Fig. 3 (right). Passivity is violated and the system tries to adapt according to the force error, see Fig. 7.

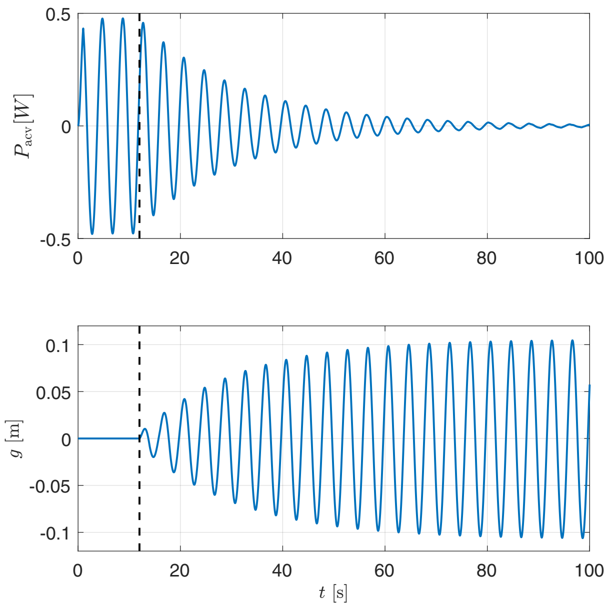

Fig. 5: In the first graph the output of the passivity observer is visualized. The second graph shows the DMP goal during learning. The vertical black dashed line depicts the start of learning.

In experiment *Sec.3* iterative learning control is applied. Within five learning cycles the system reduces the reference power error by improving passivity characteristics, which also reduces the force error by half, see Fig. 7. However, note that ILC always demands a trade-off between stability and accuracy. In the future we will investigate possibilities of automated tuning of learning parameters for sable and accurate learning. To maintain overall experimental system stability we empirically determined $K = 0.05$.

Finally, *Sec.4* visualizes the coupling term, passivity criterion and forces after learning.

VI. CONCLUSION

In this work we presented a new method for learning force-sensitive robot motion skills. Specifically, our new admittance-coupled DMP framework incorporates force feedback on trajectory level for dealing with dynamic environmental changes. Furthermore, passivity-based monitoring of reference power errors is used for learning DMP goals, helping to cope with permanent changes in the environment. The proposed method is tested in simulation and on a real robot, robustly performing a wiping task.

In future work, we will extend the stability analysis of the adaptive DMP system to cover also the iterative learning process for stable learning in several repetitions . Moreover, based on our previous work [2] frequency adaptation of the DMP can be also combined with the proposed approach.

The proposed method demands tuning of only a few parameters such as $\boldsymbol{K}$ or $\boldsymbol{D}_c$. Each one of them has a significant effect on the system behavior, but also depends on other aspects such as system architecture and control loop frequency. For the presented experiments we chose them empirically. In the future we will also investigate how to reduce and automatize parameter tuning.

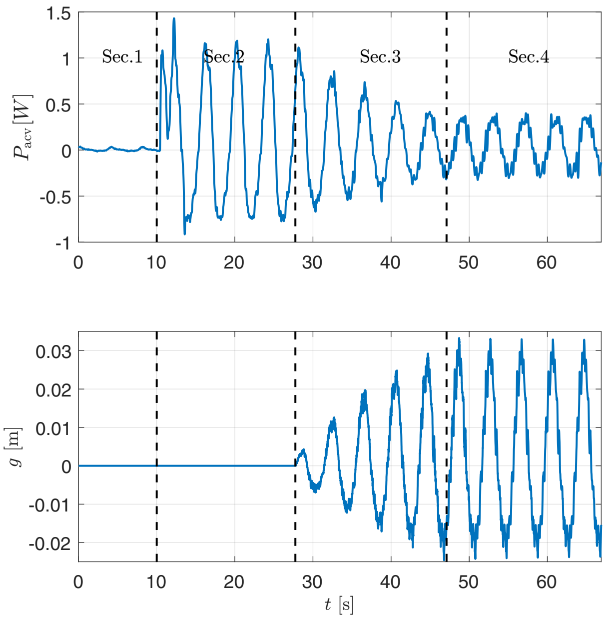

Fig. 6: The first graph depicts the evolution of system passivity. The output of the iterative learning is shown in the second graph.

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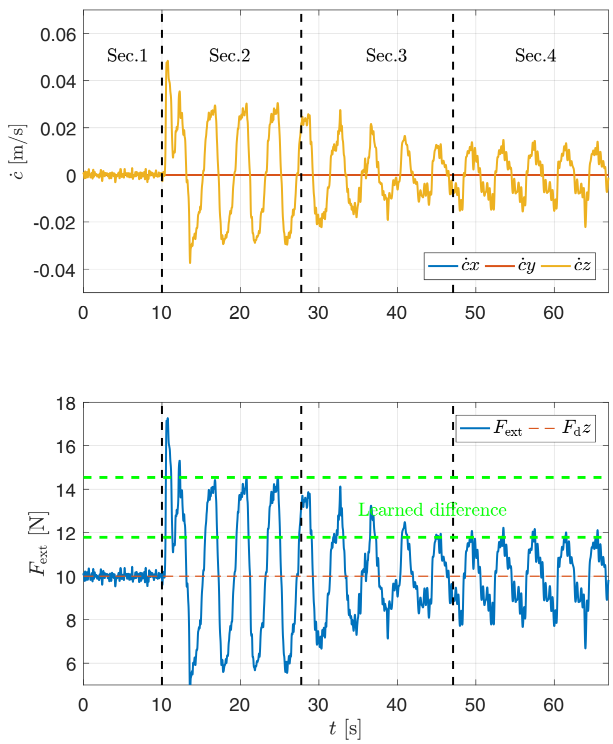

Fig. 7: The first graph shows the coupling signal, while the second graph shows the reference and measured forces during the execution of the task. The force difference after learning is depicted with green dashed lines.

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