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Human-in-the-Loop Approach for Teaching Robot Assembly Tasks Using Impedance Control Interface

Luka Peternel, Tadej Petrič and Jan Babič

***Abstract*— In this paper we propose a human-in-the-loop approach for teaching robots how to solve part assembly tasks. In the proposed setup the human tutor controls the robot through a haptic interface and a hand-held impedance control interface. The impedance control interface is based on a linear spring-return potentiometer that maps the button position to the robot arm stiffness. This setup allows the tutor to modulate the robot compliance based on the given task requirements. The demonstrated motion and stiffness trajectories are encoded using Dynamical Movement Primitives and learnt using Locally Weight Regression. To validate the proposed approach we performed experiments using Kuka *Light Weight Robot* and *HapticMaster* robot. The task of the experiment was to teach the robot how to perform an assembly task involving sliding a bolt fitting inside a groove in order to mount two parts together. Different stiffness was required in different stages of the task execution to accommodate the interaction of the robot with the environment and possible human-robot cooperation.**

I. Introduction

Robots integrated in industrial environments have been indispensable tools in many applications that require high precision and operational speed. They are mainly used to manipulate with various objects. To achieve the execution of these tasks, the robots are mostly programmed manually by experts. Such approach requires knowing of precise models of the robot, environment and their interaction.

An alternative to manual programming is robot learning such as reinforcement learning where the robot autonomously learns the task based on the given cost function [1]. The advantage of this method is that the robot can learn the task on its own. However the absence of human to supervise the learning process may lead to errors in learning and potential damage of the expensive industrial equipment.

A complement to reinforcement learning is learning by demonstration where the human simply demonstrates the skill to the robot [2]. While this method requires constant presence of the human during the entire learning process, the robots can learn new tasks faster and safer which makes this method suitable for industrial environment. One of the most common learning by demonstration approaches is kinaesthetic teaching where the human demonstrates execution of the task by simply physically holding and guiding the robot [3]. This approach is very convenient and intuitive, however it has drawbacks such as: inability to teach the robot at a distance (in case the robot is located in hazardous environment), difficulty to simultaneously control other robot parameters (e.g. impedance) and demonstrator-induced dynamics during the teaching stage.

A solution to these problems is to teach the robot through teleoperation where the human demonstrator is not physically coupled with the robot during the demonstration stage. The human can be included into the robot control loop by various haptic interfaces to provide the force feedback during the learning process. For example, these can be hand-held devices [4], [5] for teaching robotic arms of manipulation tasks [5]. In some cases, the teleoperation teaching is done without force feedback and instead relying on a combination of visual feedback and impedance control feed-forward interface [6], [7].

Currently the industrial robots mainly operate at preset high impedance. This complicates the control during the interaction with unstructured environment due to unpredictable events and external perturbations. It has been shown that human can adapt arm end-point impedance through a coordinated function of muscles to simplify the interaction with unpredictable environment [8]. This is possible due to a spring-like property of individual muscles and redundancy of antagonist muscle pairs allowing for control of joint stiffness independently of the joint torque [9]. Inspired by the advantages of human arm impedance control, researchers have proposed to control the robot arm impedance either by the means of software [10], clutches [11] or variable stiffness actuators [12].

There are numerous occasions where arm impedance has to be adjusted to achieve the desired task execution. One

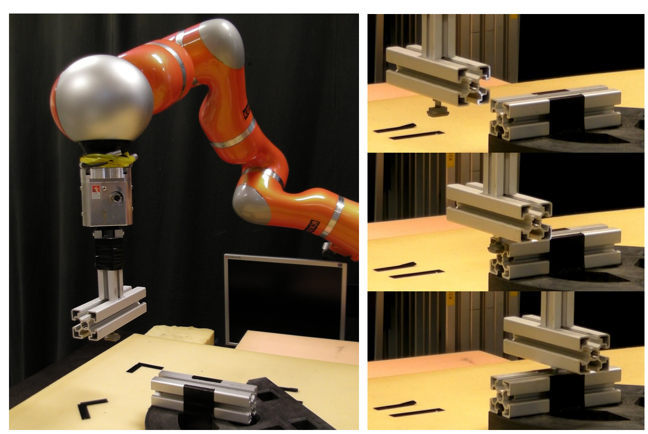

Fig. 1: Experimental setup for slide-in-the-groove assembly task. Kuka LWR holds one part with bolt fitting that has to be inserted into another part in order to fix them together.

Authors are with Department of Automation Biocybernetics and Robotics, Jožef Stefan Institute, Jamova cesta 39, 1000 Ljubljana, Slovenia luka.peternel@ijs.si

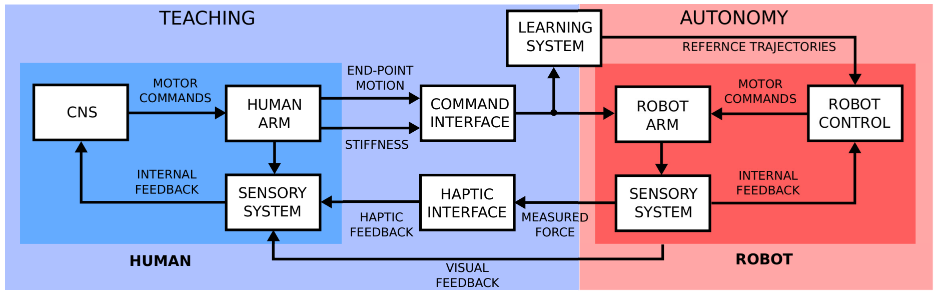

Fig. 2: Block diagram of proposed human-in-the-loop robot teaching framework. During the demonstration stage the human tutor is operating and teaching the robot through interfaces (blue section). When the learning process is complete the robot reproduces the demonstrated skill autonomously (red section).

of the prominent examples is to approach the unstructured environment with lower impedance to prevent high impact forces at the time of initial contact [4], [6], [11]. If the robot operates within the unstable environment, the impedance should be increased to achieve the expected robustness and accuracy [8]. The use of variable impedance can also maximises energy efficiency of manipulator in tasks such as object throwing [4], [13] and nail hammering [14]. Adjustments of arm impedance can simplify the execution of tasks where two agents have to cooperate with each other [7], [15]. In addition, operating at low impedance makes the robot much safer when humans intersect its workspace. One such case is human-robot cooperation where human behaviour can be unpredictable with lower repeatability.

In this paper we propose a robot teaching framework that is based around Moog *HapticMaster* robot, which measures the position of the tutor's[1] arm and at the same time provides force feedback. This classical teleoperation setup is enhanced by a novel impedance control interface that allows the tutor to modulate the robot stiffness in real-time according to the task demands. During the demonstration stage we collect the motion and stiffness data, which are learnt with periodical Dynamical Movement Primitives [16] and used for autonomous task execution. The proposed framework is intended for teaching robots how to interact with the environment for execution of various manipulation tasks. To demonstrate the applicability of the proposed approach, we performed experiments on Kuka *Light Weight Robot* (LWR) [10] arm where we taught the robot how to perform a challenging assembly task. A solution of this assembly task required the robot to insert a bolt fitting inside a groove and slide it to a certain position to fix the two parts together (see Fig. 1).

II. Experimental setup

Fig. 2 shows the block diagram of the proposed robot teaching framework. The human tutor was included into the robot control loop with a force-feedback interface on one side and with motion and impedance control interfaces on the other side. The proposed framework is based on implementation of sensorimotor learning ability of the human tutor. Specifically, human central nervous system (CNS) is capable of learning various complex tasks and tool use [17]. It has been argued that our CNS acquires and holds internal models of external the world to allow us to perform various motor control. We are able to include external objects, such as tools, into our body schema and operate with them as if they were part of our body. In the same sense the human CNS can perceive the teleoperated robot as a tool and include it into his/her body schema [7], [18].

In the experiment, we first gave the tutor some time to become proficient with the given setup and task. Then we proceeded to teaching stage where the trained tutor operated the robot by commanding both motion and impedance of the robot arm. The motion of the human arm was measured by a haptic device (Moog *HapticMaster* robot) and was sent to the robot end-effector in real-time. The forces exchanged between the robot end-effector and the environment were measured by the robot sensory system and were fed back to the human through a haptic device. At the same time tutor used visual feedback to determine the state of the robot arm. When demonstrating the task, the learning system stored the data about the task execution. This data was then used to generate DMP trajectories of the robot end-effector motion and stiffness, which were then used to execute the task autonomously.

With the proposed approach we aim to teach industrial robots various interaction tasks. Since the majority of industrial tasks are of repetitive nature, we chose to use periodic DMPs [16] to encode these actions. The trajectories were normalised to phase of periodic cycle, which allowed us to arbitrary slow down or speed up the different sections of the cycle. In addition, we were able to stop at some predefined phase in order to make some additional action, such as tightening the bolt in the assembly task.

A. Trajectory learning system

Here we give a short recap of the DMPs. They are based on a second order system of differential equations [16]

$$\dot{z} = \Omega\left(\alpha_z\left(\beta_z(-y) - z\right) + f\right), \tag{1}$$

$$\dot{y} = \Omega z, \tag{2}$$

where y is the trajectory, Ω is the frequency, f is the nonlinear shape function, which alters the second order

[1]Tutor is a teleoperator with the aim to teach the robot a new behaviour.

differential equation, and α_z and β_z are positive constants. Gaussian kernels are used to produce shape f

$$f(\phi) = \frac{\sum_{i=1}^{N} \psi_i(\phi) w_i}{\sum_{i=1}^{n} \psi_i(\phi)}, \tag{3}$$

Gaussian kernel $\psi_i(\phi)$ is phase dependant and defined as

$$\psi_i(\phi) = e^{h(\cos(\phi - c_i) - 1)}. \tag{4}$$

where parameter h is the width of Gaussian kernel, c_i are the uniformly distributed centres of the kernels across the phase (between 0 and 2π), and N is the number of weights. Number of weights determines the desired resolution of trajectory. For our experiments we selected 50 weights.

Locally Weighted Regression [19] was used to learn the shape function f as described in [20]

$$f_d = \frac{\ddot{p}_d}{\Omega^2} - \alpha_z \left(\beta_z (-p_d) - \frac{\dot{p}_d}{\Omega} \right). \tag{5}$$

where p_d, $\dot{p}_d$ and $\ddot{p}_d$ are the desired commanded motion and stiffness and their derivatives. Weights w_i of Gaussian kernel functions ψ_i are updated using a recursive least squares method with forgetting factor λ [19]

$$w_i(t+1) \quad = \quad w_i(t) + \Psi_i P_i(t+1) r e_r(t), \tag{6}$$

$$e_r(t) = f_d(t) - w_i(t) r, \tag{7}$$

$$P_i(t+1) = \frac{1}{\lambda} \left(P_i(t) - \frac{P_i(t)^2 r^2}{\frac{\lambda}{\Psi_i} + P_i(t) r^2} \right), \tag{8}$$

where the parameters were initially set as $w_i(0) = 0$, $P_i(0) = 1$, $i = 1, 2, ..., N$. For the purpose of our experiments we selected $\lambda = 0.99995$.

B. Impedance control interface

Several studies in the past explored the teleoperation scenario or robot teaching framework where the teleoperator/tutor had the ability to voluntarily adjust the robot impedance in real-time. Ajoudani et al. [6] used human muscle activity signals from antagonistic pairs to estimate multi-axis impedance of the teleoperator's arm end-point. This estimation was then mapped to the robot end-effector impedance. Peternel et al. [7] proposed a simplified single-muscle impedance control interface for a robot teaching framework. Human muscle activity based interfaces are effective but they require time-consuming calibration procedures and knowledge of human anatomy. This can make them less suitable for industrial application.

Walker et al [11] proposed to control the impedance of a 1DOF system in a teleoperation scenario using hand grip force sensor. With this interface the human simply squeezed the handle of the haptic device to modulate the impedance. This makes the approach very suitable for industrial use. However it has been shown that muscle fatigue can degrade the performance of grip force production [21], [22]. Prolonged use of hand grip as impedance control interface induces fatigue that can lead to a lower performance.

Fig. 3: Robot control interface consisting of *HapticMaster* robot and impedance control handle. *HapticMaster* robot measured commanded position and provided the force feedback. Impedance control handle contains a spring-return linear potentiometer and is held in tutor's hand.

Based on this potential drawback we propose a new impedance control interface for the robot teaching framework (see Fig. 3). This interface uses a spring-return linear potentiometer mounted inside a handle that is held in the tutor's hand. The tutor uses index finger to control the position of the potentiometer push-button. This setup retains the simplicity and applicability of the grip-force interface [11], while the finger position based input requires little effort from the tutor. In addition, a potentiometer is a low-cost device compared to a grip-force sensor.

The position-related potentiometer voltage was read with AD converter and mapped to the robot end-effector stiffness. The mapping is described as

$$K = \frac{V(t)^2}{V_{max}^2} \left(K_{max} - K_{min} \right) + K_{min}, \tag{9}$$

where K is robot stiffness, $V(t)$ is potentiometer voltage at time t, V_{max} is maximal voltage and K_{max} and K_{min} determine the controllable stiffness range. As opposed to [7], where a linear mapping was used, we used quadratic mapping to give more sensitivity to the low-stiffness section of the range.

In our case, we altered the robot impedance by changing the virtual stiffness in the robot position control. The force that robot exerts on an external object is generated by moving the reference (commanded) position inside the object to achieve a displacement between the actual robot position (blocked by the object surface) and reference position inside the object. The desired interaction force is defined by the current value of stiffness and the displacement between the commanded (referent) and actual position

$$F_d = K \big(x_r - x_a(env) \big), \tag{10}$$

where F_d is the interaction force acting between the robot and the environment, K is robot stiffness in cartesian space, $x_a(env)$ is actual and x_r is reference position of the robot end-effector. The actual position $x_a(env)$ also depends on

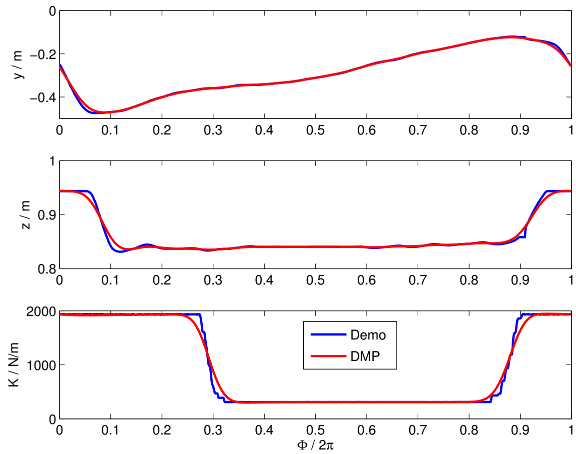

Fig. 4: Result of slide-in-the-groove assembly task teaching. The top graph shows position trajectory of robot end-effector in y-axis (along the groove). The middle graph shows (vertical) z-axis position trajectory. The bottom graph shows stiffness trajectory. The blue lines correspond to the trajectory formed from the demonstrated training data while the red lines correspond to the learnt DMP trajectory.

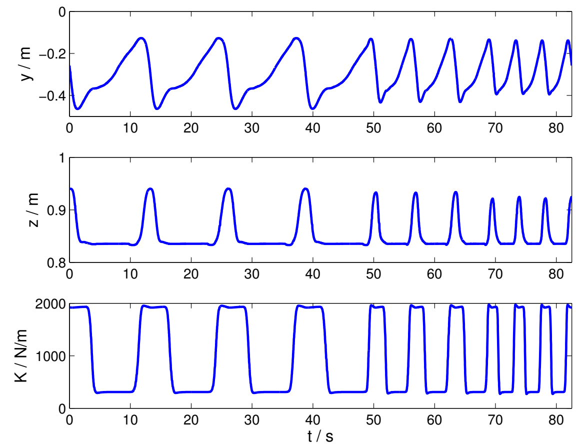

Fig. 5: Result of task execution speed adjustment. The top graph shows the measured robot end-effector y-axis position trajectory. The middle graph shows the measured z-axis position trajectory. The bottom graph shows the commanded stiffness trajectory.

the environment. The desired interaction force in cartesian space was controlled at the robot joint torque level

$$\tau = J^T F_d + \tau_{dyn}(q, \dot{q}, \ddot{q}), \tag{11}$$

where τ is a vector of robot joint torques, q is vector of joint angles, J is robot Jacobian matrix and $\tau_{dyn}(q, \dot{q}, \ddot{q})$ term accounts for the dynamics of the robot. Given that we know the inverse dynamics model of the robot $\tau_{dyn}(q, \dot{q}, \ddot{q})$, we can calculate the necessary joint torques τ to produce the desired interaction force F_d.

The desired force that the robot exerts on the environment can be achieved by different combinations of the desired end-effector position and stiffness. This redundancy provides many task-related benefits, which were stated in the introduction. On the other hand, the ability to command the robot impedance can provide additional teaching-level benefits. Tutor can exploit the ability to directly control the stiffness to minimise the force-feedback related instability of teleoperation setup. Induced motion by force feedback combined with delays in teleoperation loop can destabilise the teleoperator's arm and cause oscillations [23]. Several solutions has been proposed to stabilise the teleoperation [23], [24].

In this paper, we propose to exploit the ability to directly control the impedance combined with the aforementioned force-control redundancy to stabilise the force-feedback teleoperation. The tutor can scale the sensitivity of feedback force to variation in commanded position by changing the stiffness of the robot end-effector. Commanding low robot stiffness during the contact reduces the undesirable effect of force-feedback induced motion. This is because, at lower K, the variation in commanded position, as a result of induced motion, produces lower variation of force measured between the robot and the environment, which in term produces lower variation in feedback force.

III. Experiments

Assembly of an object from various parts is one of the common industrial tasks. It may involve various elementary sub-tasks that require adaptation of robot arm impedance. One of the examples is a peg-in-the-hole task that has been extensively studied in the past [4], [6], [15], [25]. The usual strategy for solving the peg-in-the-hole task is to first approach the hole with a low impedance, in order to reduce the force of impact and allow the peg to fit into the hole, and then increase the impedance to push the peg inside a tight spot.

A similar elementary task is fixing two parts together with bolt fittings. This requires inserting a bolt fitting inside a groove of the complementary part and sliding it to a position where the bolt is to be fixed to hold the two parts together (see Fig. 1). To solve a slide-in-the-groove task, we designed a strategy where the impedance of the robot arm increases when it is moving the part in air in order to provide the stabilisation and robustness to potential external perturbations [8]. When the robot approaches the groove the impedance should be decreased to minimise the impact forces [4], [6], but should be kept high enough to offer the precision required for the insertion of the bolt. While sliding to the fixation position the impedance was kept low as the rigid environment itself (i.e. the groove) provided the necessary stabilisation for the robot. At the same time, low impedance provided a preventive strategy against unpredictable events. For example, if the base part with the groove moves when robot impedance is high, it produces high forces between the bolt fitting and the groove. Such events may potentially make the bolt stuck or even damage the equipment.

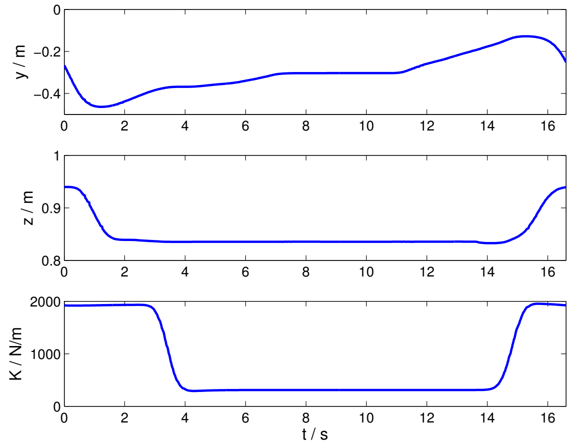

Fig. 6: Result of assembly task execution where phase was halted for purpose of bolt fixation. The top graph shows the measured robot end-effector y-axis position trajectory. The middle graph shows the measured z-axis position trajectory. The bottom graph shows the commanded stiffness trajectory.

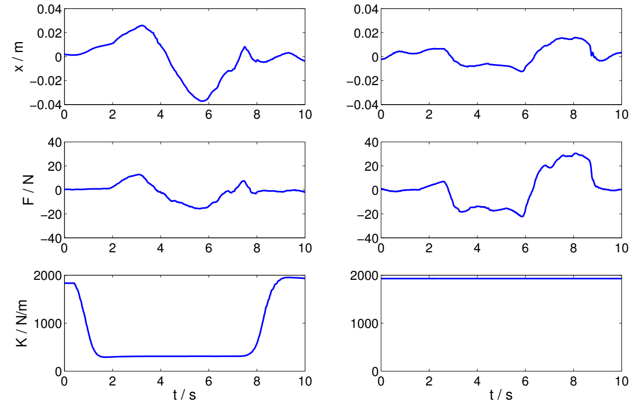

Fig. 7: Result of perturbation experiment for demonstrated variable robot impedance (left column) and preset high impedance (right column). The top row graphs show the displacement of robot end-effector x-axis position from the commanded reference position. The middle row graphs show the measured force in x-axis as a result of perturbation. The bottom row graphs show the commanded stiffness.

In the experiment we instructed a trained tutor to teach the robot how to perform the given slide-in-the-groove task according to the designed strategy. During the teaching procedure we collected training data consisting of commanded robot end-effector position and stiffness. After the demonstration stage we proceeded to robot learning stage where the data was used to form trajectories which were normalised to phase and encoded with periodic DMPs. Fig. 4 shows the trajectories formed from the demonstrated data (blue lines) and their corresponding DMPs (red lines). We then used the DMPs to reproduce the learnt repetitive behaviour and perform the desired task. Multimedia accompanying this paper contains a video of this experiment.

After the learning stage the robot executed the demonstrated task autonomously. The learnt trajectories were controlled by a phase input, which was a repetitive ramp signal rising from 0 to 2π. During this process we can control the speed of trajectory execution by changing the frequency of phase signal. In this experiment we demonstrated the ability to arbitrarily change the task execution speed by switching between three different DMP periods. The results of this experiment are shown in Fig. 5. The upper two graphs show the measured robot end-effector position, while the lower graph shows the commanded robot stiffness.

We controlled the phase of DMPs to make a stop at the point where the bolt fitting should be tightened to fix the two parts together. The stopping point is time-independent and is determined by the phase, therefore the fixation point is uniquely and precisely defined with respect to the position. The results of this experiment can be observed in Fig. 6. The trajectory was reproduced at a predefined execution frequency. The frequency was set to 0 Hz at the phase where the robot reached the point of bolt fixation. This occurred at 6.5 seconds on the localised time scale. The phase control signal frequency was then kept at 0 Hz for 5 seconds for the purpose of tightening the bolt. At 11.5 seconds the trajectory execution was resumed by setting the frequency back to the execution frequency. The learned trajectories can be further coupled with adaptive oscillators if the task requires frequency adaptation to some external variable [7], [20], [26].

To demonstrate the advantage of low robot impedance, while sliding inside the groove, we perturbed the base part by manually displacing it. With this we emulated instances such as human-robot cooperation and unpredictable events that may occur in real world scenarios. In the first trial we used the impedance as demonstrated by the tutor, i.e. high impedance during the movement of the part in the air and lower impedance while sliding the bolt inside the groove (see Fig. 7, lower left graph). In the second trial we used a preset constant high impedance at the point of perturbation (see Fig. 7, lower right graph).

By observing the relations between the displacement of end-effector position from the commanded reference position (Fig. 7, first row) and resulting forces (Fig. 7, second row), we can see that the preset high impedance during the sliding inside the groove produced relatively high forces even in case of small positional displacements. Exposing such system to strong perturbations could lead to damage of the equipment. In several occasions the high force resulted in bolt being stuck inside the groove. In contrast, robot produced relatively lower forces for the same level of positional displacements when using the demonstrated low impedance. Such method offers much safer operational conditions for the autonomous task production in an unpredictable environment or human-robot cooperation scenario.

IV. Disscussion

In the proposed method the human directly sets the impedance of the robot by commanding the stiffness trajectory using the given feed-forward interface. In contrast, some learning techniques use the variability of the demonstrated position trajectories to estimate the impedance of the robot [5], [27]. These studies suggest that the impedance should be low if the demonstrated trajectories have a high variance, while the impedance should be high if the demonstrated trajectories have a low variance. This strategy can provide a very good solution for many manipulation tasks. The advantage is that you do not need to demonstrate the impedance separately. However in some of the interaction tasks, such as slide-in-the-groove task, the low trajectory variability does not necessarily correspond to the high impedance. As we showed in our experiment, the impedance can be low despite the low trajectory variability, because the low variability results from the robot being stabilised and constrained by the environment. Therefore in this particular case, allowing the tutor to directly modulate the impedance is advantageous.

V. Conclusion

We proposed a human-in-the-loop framework for teaching robots how to solve assembly tasks involving interaction with environment. Classical force-feedback teleoperation setup was complemented with a novel impedance control interface based on a linear spring-return potentiometer. We used this framework to teach the robot how to perform an assembly task where the bolt fitting attached to one part had to be inserted and moved inside the groove of another part. The collected training data was used to learn DMPs which were used to reproduce the demonstrated actions in the autonomous stage. With the experiments we demonstrated the advantages of directly teaching the robot how to modulate impedance at different stages of the given assembly task.

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