A Framework of Hybrid Force/Motion Skills Learning for Robots

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A Framework of Hybrid Force/Motion Skills Learning for Robots

Ning Wang, *Member, IEEE,* Chuize Chen, Alessandro Di Nuovo, *Senior Member, IEEE*

***Abstract*—Human factors and human-centred design philosophy are highly desired in today's robotics applications such as human-robot interaction (HRI). Several studies showed that endowing robots of human-like interaction skills can not only make them more likeable but also improve their performance. In particular, skill transfer by imitation learning can increase usability and acceptability of robots by the users without computer programming skills. In fact, besides positional information, muscle stiffness of the human arm, contact force with the environment also play important roles in understanding and generating human-like manipulation behaviours for robots, e.g., in physical HRI and tele-operation. To this end, we present a novel robot learning framework based on Dynamic Movement Primitives (DMPs), taking into consideration both the positional and the contact force profiles for human-robot skills transferring. Distinguished from the conventional method involving only the motion information, the proposed framework combines two sets of DMPs, which are built to model the motion trajectory and the force variation of the robot manipulator, respectively. Thus, a hybrid force/motion control approach is taken to ensure the accurate tracking and reproduction of the desired positional and force motor skills. Meanwhile, in order to simplify the control system, a momentum-based force observer is applied to estimate the contact force instead of employing force sensors. To deploy the learned motion-force robot manipulation skills to a broader variety of tasks, the generalization of these DMP models in actual situations is also considered. Comparative experiments have been conducted using a Baxter Robot to verify the effectiveness of the proposed learning framework on real-world scenarios like cleaning a table.**

***Index Terms*—Robot learning, skill transfer, dynamic movement primitives, force observer, hybrid force/motion control, generalization**

I. Introduction

THE rapid development of artificial cognitive systems and robotics is enabling increasingly intelligent robots to physically operate into more demanding and wider application domains, ranging from industrial manufacturing to social care [1]. These new challenges require not only safer operation, but also more precise motor control and fine manipulation skills for navigating and interacting within complex environments, often populated by human beings. In many cases, cognition-enhanced robot learning ability is required. In some scenarios, robots are expected to work together with human beings, where compliant performance and human-friendly user experience are desired, e.g., [2], [3]; while in others, robots are expected to autonomously conduct tasks like human beings, e.g., [4]. By using game theory and policy iteration, the human being's control objective can be estimated in the human-robot interaction process [5]. In the future, robots will be deeply integrated into more aspects of human life, which requires robots to have more dexterous skills to provide more friendly interaction and services [6].

In this context, it is crucial for the future generation of robots to acquire the ability of flexbile interaction with human beings. In fact, besides designing and building robotic systems that guarantee safe interaction, robots must be provided with further qualities that are common for humans [7]. This suggests that future robots should own human-like learning and generalization ability without increasing the cognitive workload of the user [8], [9]. At present, most commercial robots require either specific computer knowledge or teaching pendants to complete robot programming. When a robot meets new environments or different users, all manipulation information have to be updated accordingly in order to complete the new task. However, reprogramming robots is a time-consuming job and requires certain level of techniques, which can be difficult for ordinary robot users, such as factory workers, or elderly people in care home. This has been a hurdle in popularizing and promoting robots for many years. It is, therefore, crucial to develop a smart, intuitive and user-friendly way to interact, to teach and to equip robots with new skills.

For more intuitive human-robot interaction, it is essential that the intention of the human partner can be inferred and addressed naturally, like in human-human interaction [10]. In the long run, a robotic system will not be accepted as a natural, human-like partner if it does not learn new tasks by itself and adapt during the interaction. A good strategy is to directly learn from the interaction partner, i.e., the human being. This approach is called imitation learning [11], and aims at overcoming the difficulty of transferring skills from humans to robots, which is inspired by the way humans learning skills via mirroring and practice [12]. Robot programming by demonstration (PbD) is an efficient way to achieve robot learning in an intuitive manner, which simultaneously considers the task and environment [13]. The main idea of skills transferring is accomplished through reproducing the tasks from human

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demonstrator directly to the robot, or adapting prior learnt motion models by generalization techniques. The former is easy to understand but not always feasible because of the mismatching between robot joints and human arm joints, as well as the lack of scalability. Through modelling the human demonstrations, the match between human skills and robots can be improved, and the demonstrated manipulation can be further generalized to suit various applications.

In general, there are two approaches of PbD: probability-based approach and dynamic system (DS)-based approach [14]–[16]. The probability-based approach seeks to encode the probability distribution of motions in space [17]–[19], while the DS-based approach provides more flexible implementation, where a DS is employed to encode the motion profiles. Meanwhile, the motion will end up at the desired position point. The dynamic movement primitives (DMPs) model is a typical method in DS-based approach, which has been widely applied in the field of PbD [20], [21]. The DMPs model a motion primitive as the evolution of a spring damper system that is driven by a virtual force. The end of the motion is controlled by the spring damper system while the profile of the motion depends on the virtual force. The superiority of this method lies in its generalizability, meanwhile it regulates any motion by parametrizing only the start and the end positions of motion.

Human motor skills is conveyed by several other information sources beside motion, i.e., positional information, to name a few, the muscle stiffness, the contact force with the environment, etc. In the efforts of human-to-robot skills transfer, these multiple information sources should be included as well. The DMPs have already been successfully employed in building motion and stiffness profiles respectively. Evidences show that by modelling and combining these two information sources together, the robot learning outcome has been improved [22]. The motion of a robot is easy to capture considering most robots are equipped with position sensors. On the other hand, contact forces are measured through force sensors, however, a robot is not always fitted with one. Note that muscle stiffness or electromyographic (EMG) signals can only reflect contact force indirectly. This will inevitably introduce noises, and cause robot control errors. To avoid increasing system complexity, momentum-based force observers have been introduced to replace force sensors in many cases. Generally speaking, a momentum-based force observer usually offers good accuracy, because it doesn't require knowledge of joint acceleration since its sensitivity is independent of joint position [23]. Therefore, in this paper, we estimate the contact force by a momentum-based force observer first, and then simulate the estimated quantity by building DMP models. Through combining these DMPs-modelled force profiles with the widely used motion DMP models, we can achieve a robot manipulation that benefits from both the motion and force footprints simultaneously. This will be highly desirable in force-related tasks like floor mopping, window cleaning, etc. A Kalman filter is applied later on for curve smoothing purpose, and a hybrid force/motion controller is introduced in this framework to reproduce the demonstrated motion and force skills. To our best knowledge, there is little research work on modelling both the motion trajectories and contact force profiles for skills transfer. To this end, the proposed scheme not only can improve robot skills, but also will keep the system complexity to the minimum without involving an additional force sensor.

The contributions of this paper are summarized as follows:

- *Motor skill representation*: Along with the widely employed DMP models of motion, the framework simultaneously elaborates DMP models for the contact forces to provide comprehensive representation of human motor skills.
- *Motion-force control scheme*: A hybrid force/motion controller is applied to reproduce the modelled motion and force profiles, which results in higher success rate in performing tasks than that with motion data only. This includes a momentum-based force observer for the reduction of system complexity.
- *Cognitive learning framework*: A comprehensive framework is built to support generalization and to equip robot with multiple human skills from human demonstrations in a simpler, user-friendly manner.

The rest of this paper is organized as follows: next section introduces the related work of PbD and force observer. The skill transfer framework and the methodology are introduced in Section III. The experimental study is presented in Section IV. Section V finally concludes this work.

II. Related Work

Robot programming by demonstration has been proven to be a well accepted way of transferring human motor skills to a robot [11], where the robot gains skills by imitating what the human tutor demonstrates. The research of PbD involves the demonstration techniques, such as teleoperation [24], [25] and shadowing [26] and policy derivation techniques [27]. Nowadays, most of works focus on the latter, which replies on the demonstration data to estimate any unknown underlying function mappings from human observation to robot action. In [28], a template-based approach using minimum energy strategies for robot movement imitation has been proposed. This work has been further extended to incorporate some relative merits of system models by decomposing the demonstration and recording the associate constraints of a series of primitive templates [29].

In general, policy derivation techniques can be categorized into two types (classification-based and regression-based approaches, respectively) according to the mapping output (continuous or discrete). The classification-based methods are applied at the motion primitives level, where various classifiers such as Gaussian Mixture Models (GMMs) [30], decision trees [31], Bayesian network [32] and k-Nearest Neighbors (kNN) [33] are employed, to decide which primitive will be adopted. The regression-based methods are generally taken in presenting lower level motions. Pure regression-based methods like Locally Weighted Projection Regression (LWPR) [34], [35] have been successfully applied on robots performing the ball seeking task [36] and on humanoid robots playing the air hockey game [37]. However, this type of methods mainly

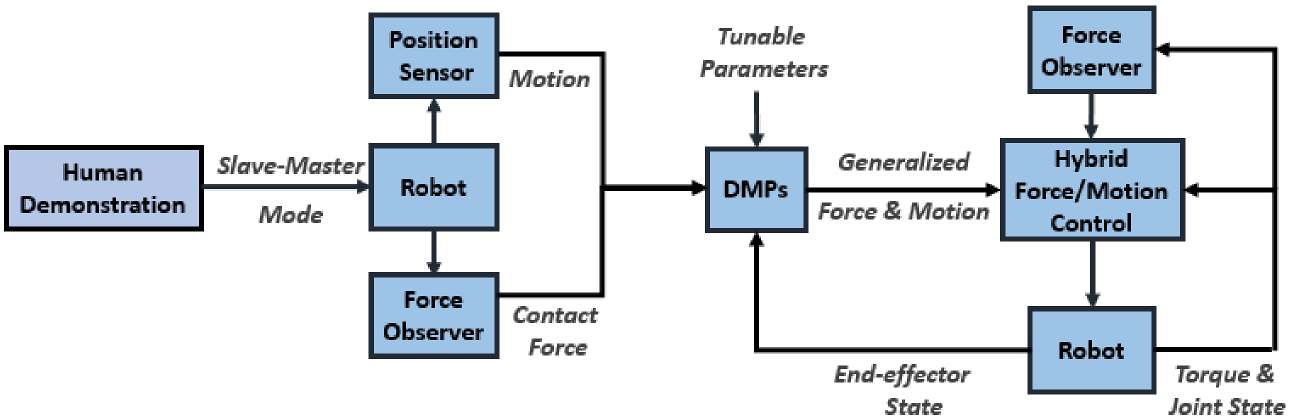

Fig. 1. Illustration of the proposed skill transfer framework from human to robot.

focuses on repeating demonstrations in essence, having little generalizability.

DMP models are capable of combining the merits of the regression-based approach with the dynamic system to enhance the all important generalization ability. Thanks to its desirable characteristics of one-shot learning and real-time stability, many variants of DMPs have been developed. In [38], a method called Compliant Parametric Dynamic Movement Primitives (CPDMP) has extended DMPs, enabling it to perform parametric learning on complex motion. In [39], [40], a method called DMP Plus has been proposed to achieve lower mean square error and efficient modification at the same time. The DMPs method has also been enhanced by reinforcement learning (RL) technique in achieving motion tuning [41].

Only reproducing and generalizing the motion profile of demonstrations could not meet the need of completing complex tasks in various working environments. Therefore, methods involving other information sources in skills learning have been proposed. The stiffness clues extracted from human EMG signals have been modelled by DMPs to deliver stiffness-specific skills [22]. In [42], the force-related information was considered in adapting the weights of DMPs. In [43], RL technique has been applied to fine-tune the discretized force trajectories in order to better perform the given task. Compared to the stiffness estimated from muscle EMGs, force profiles are more direct to capture and closely connected with human skill representation and modelling. Considering the force modelling and generalization has not been well discussed, and the merits of DMPs in tracking robot features, in this work, we further extend the skills representation to include force features modelled by DMPs, in addition to the stiffness profiles as in [6]. This paper presents a framework that enables a robot to learn both movement and force-related characteristics from the human tutor all at once, and be able to apply these learnt skills flexibly to accomplish tasks requiring both force- and motion-specific skills.

During robot manipulation, contact forces endured by the end-effector are not easy to measure considering tool interference. Indirect measurements like that from wrist-mounted force sensors are likely to be contaminated by inertial forces. Various approaches have been developed to estimate the contact force between the robot and the environment. Among them, the most straightforward method is to compute the external torque from robot dynamics model directly. However, this method requires knowledge about the joint acceleration. Although the acceleration value is obtainable by using acceleration sensors [44] or by double differentiating the joint position, it might introduce large noises in this way. The torque can also be acquired through analysing desired trajectories and inverse dynamics of the robot, however, it requires great tracking performance of robots. In [45], a joint velocity observer is proposed to estimate the external force. However, the filter equation is nonlinear and coupled because of the calculation of the inverse inertia matrix. Compared with methods mentioned above, the momentum-based force observer requires neither acceleration nor inverse inertia matrix, and the resultant filter equation is linear [46]. Considering these advantages, in this work, a momentum-based force observer is developed and taken to estimate the incurred contact force.

III. Methodology

A. Overview of the Framework

The proposed framework is shown in Fig. 1, which can be divided into three parts: a) demonstration, b) modelling and generalization, c) reproduction.

Demonstration – In the demonstration phase, the skills to complete the given task are demonstrated under the slave-master mode, which will be introduced in details in Section IV. The robot motion is measured by a position sensor, and the contact force is estimated by the force observer.

Modelling and Generalization – In this phase, the motion and the contact force obtained in the demonstration phase are modelled by individual DMPs, respectively. The generalization of the motion and contact force profiles can be achieved by tuning the parameters of the learnt DMP models.

Reproduction – Due to the joint usage of the motion and the force, the hybrid force/motion controller is used to track the desired motion and force (generated from their DMPs). The force observer is employed to provide feedback information.

B. Robot Programming by Demonstration

In this section, the DMPs that involve in modelling motion and contact force are introduced. Since the modelling of force is the same as that for motion (by regarding the variant of force as a trajectory), we will introduce the motion modelling in details and highlight only the points that should be considered for force modelling.

1) DMPs for Motion Planning: The DMP model for task-space motion is defined as follows [21],

$$\begin{aligned} \tau_d \dot{v} &= \alpha(x_g - x) - \beta v + \alpha\left[f(s) - (x_g - x_0)s\right] \\ \tau_d \dot{x} &= v \end{aligned} \tag{1}$$

where $x \in R$ is the position state in Cartesian space, $v \in R$ and $\dot{v} \in R$ are the Cartesian velocity and acceleration, respectively. x_0 and x_g are the initial position and the goal position, respectively. $\alpha, \beta \in R$ are the positive constants to be specified, $\tau_d > 0$ is the temporal-scaling factor, and $s \in R$ denotes the state of the canonical system [21], which is a DS defined as in (2),

$$\tau_d \dot{s} = -\gamma s \tag{2}$$

where $\gamma > 0$ denotes the decay rate. The initial state of the canonical system is set as $s_0 = 1$. $f(s)$ is a continuous nonlinear function pre-defined as in (3) [21],

$$f(s) = \sum_{i=1}^{n} \omega_i \psi_i(s) s \tag{3}$$

with

$$\psi_i(s) = \frac{\exp\left[-(s - b_i)^2/(2c_i)\right]}{\sum_{i=1}^{n} \exp\left[-(s - b_i)^2/(2c_i)\right]} \tag{4}$$

where $\psi_i(s)$ is the normalized Gaussian function with the mean $b_i \in R$ and the variance $c_i \in R$. n is the number of Gaussian functions. $\omega_i \in R$ is the weight of the i-th Gaussian function.

The DMP model can be regarded as a spring-damper system driven by a virtual external force, with the magnitude described as in (5),

$$K_f = \alpha\left[f(s) - (x_g - x_0)s\right] \tag{5}$$

where $(x_g - x_0)$ serves as the spatial-scaling factor. Since s in (2) is monotonically decreasing and will converge to zero with the initial value $s_0 > 0$, $f(s)$ and K_f will converge to zero, and the position state x will evolve to the attractor x_g, which means that the goal of the motion can be modified by changing x_g. Besides, the duration of the motion is determined by the factor τ_d. These two characteristics are requisite for a generalizable motion model.

Assuming that the demonstration is generated from the DMP model, the parameters of the model can be learned by solving a linear regression problem. The expected nonlinear function of $f(s)$ is defined as follows [21],

$$f^*(s) = \frac{\tau_d \ddot{x}(\bigtriangledown_s) + \beta \dot{x}(\bigtriangledown_s)}{\alpha} - (x_g - x(\bigtriangledown_s)) + (x_g - x_0)s \tag{6}$$

where $x(\cdot)$ denotes a given demonstration trajectory, which is assumed as a function of time. $\bigtriangledown_s$ denotes the inverse function of $s(t) = s_0 \exp(-\gamma t/\tau_d)$, which is the solution of (2). With the data obtained from (6), the weight vector $\omega = \{\omega_1, ..., \omega_n\}$ can be estimated by using the least squares method.

2) DMPs for Force Modulation: By regarding the variation of contact force as a trajectory, we can use a similar DMPs method to model contact force, like what we do for modelling the motion. The process is described by (7)

$$\begin{aligned} \tau_d \dot{F}_v &= \alpha(F_g - F) - \beta F_v + \alpha\left[f(s) - (F_g - F_0)s\right] \\ \tau_d \dot{F} &= F_v \end{aligned} \tag{7}$$

where $F \in R$ is the contact force and $F_v \in R$ is the rate of change of F. F_0 and F_g is the initial value and the final value of the contact force, respectively. The setting of α and β here are independent of (1). The DMPs for contact force share the same temporal factor τ_d and the canonical system (2) with the model of motion to keep synchronization of time. Likewise, by tuning the temporal-scaling factor and the goal position parameter, the variant of contact force can also be generalized.

C. Momentum-based Force Observer

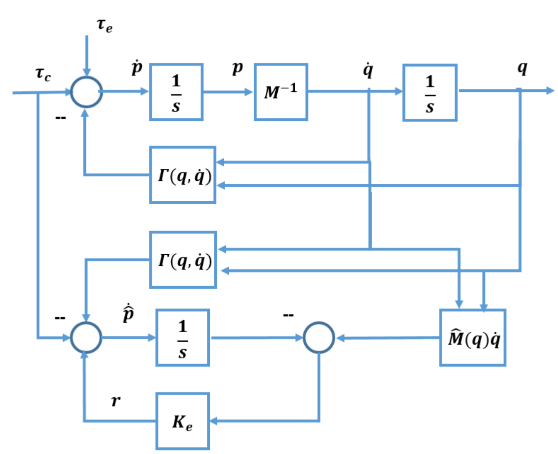

Fig. 2. Illustration of the momentum-based force observer.

In this section, the momentum-based force observer [23] and the Kalman filter are introduced.

The dynamic model of a robot manipulator is defined as in (8),

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) + \tau_e = \tau_c \tag{8}$$

where $M(q) \in R^{n \times n}$ is the inertia matrix, $C(q, \dot{q})\dot{q} \in R^n$ is the centripetal and Coriolis vector and $g(q) \in R^n$ is the gravity vector. τ_c represents the control torque and τ_e represents the external torque.

The momentum of the robot is defined as in (9),

$$p = M(q)\dot{q} \tag{9}$$

Then, the derivative of the momentum can be written as follows,

$$\begin{aligned} \dot{p} &= \dot{M}(q)\dot{q} - C(q, \dot{q})\dot{q} - g(q) + \tau_c + \tau_e \\ &= C^T(q, \dot{q})\dot{q} - g(q) + \tau_c + \tau_e \end{aligned} \tag{10}$$

In (10), the i-th component of $\dot{p}$ is defined as follows,

$$\dot{p}_i = -\frac{1}{2}\dot{q}^T \frac{\partial M(q)}{\partial q_i}\dot{q} - g_i(q) + \tau_{c,i} + \tau_{e,i} \tag{11}$$

for $i = 1, ..., n$, which means that each component is only affected by the corresponding component of the torques.

The generalized momentum-based observer monitoring method introduced in [46] and [47] is designed to avoid the inversion of the robot's inertia matrix, to decouple the estimation results, and to avoid the estimation of joint acceleration. Define the quantity as in (12),

$$\begin{aligned}\Gamma(q,\dot{q}) &:= C(q,\dot{q})\dot{q} - \dot{M}(q)\dot{q} + g(q) \\ &= -C^T(q,\dot{q})\dot{q} + g(q)\end{aligned} \tag{12}$$

The momentum observer dynamics can be written as in (13),

$$\begin{aligned}\dot{\hat{p}} &= \tau_c - \hat{\Gamma}(q,\dot{q}) + r \\ \dot{r} &= K_e(\dot{p} - \dot{\hat{p}})\end{aligned} \tag{13}$$

where $K_e = \operatorname{diag}\{k_{e,i}\} > 0$ is the gain matrix of the observer. r is the output of the observer, and it can further defined as below,

$$\begin{aligned}r &= K_e\left(p(t) - \int_0^t \dot{\hat{p}}(s)\mathrm{d}s - p(0)\right) \\ &= K_e\left(p(t) - \int_0^t \left(\tau_c - \hat{\Gamma}(q,\dot{q}) + r\right)\mathrm{d}s - p(0)\right)\end{aligned} \tag{14}$$

with $p = \hat{M}(q)\dot{q}$. Assuming that $\hat{M} = M$ and $\hat{\Gamma} = \Gamma$, the dynamic relation between the output r and the external joint torque τ_e can be written as in (15),

$$\dot{r} = K_e(\tau_\mathrm{e} - r) \tag{15}$$

By applying the Laplace transformation, we have:

$$r_i = \frac{k_{e,i}}{s + k_{e,i}}\tau_{e,i} = \frac{1}{1 + T_{e,i}s}\tau_{e,i}, \quad i = 1, \ldots, n \tag{16}$$

Thus, large values of $k_{e,i}$ give small time constants $T_{e,i} = 1/k_{e,i}$ in the transient response of the component of r, which is associated with the same component of the external torque τ_e. Within the limit, we can obtain $r \approx \tau_\mathrm{e}$ when $K_e \to \infty$. The diagram of the force observer is shown in Fig. 2.

As analyzed above, this good characteristic makes the momentum observer a virtual sensor for external joint moments acting on the robot structure. By using the Jacobian matrix, the external force F_e can be transformed from the external torque.

Since the external force estimate contains some noises, the Kalman filter is applied to smooth the force estimate F_e, which can be written as below,

$$F_e(t) = h(t)\hat{\theta}(t) \tag{17}$$

where $\hat{\theta}(t)$ is the estimated parameter vector of Wiener filter coefficients and $h(t)$ is the virtual input. The Kalman filter estimation law is described as follows [48],

$$\begin{aligned}K(t) &= P(t)h^T(t)R^{-1}(t) \\ \dot{P}(t) &= -K(t)h(t)P(t) \\ \dot{\hat{\theta}}(t) &= K(t)\left[F_e(t) - h(t)\hat{\theta}(t)\right]\end{aligned} \tag{18}$$

where $K(t)$ is the filter gain, $P(t)$ is the covariance, $\hat{\theta}(t)$ is the estimated filter parameter vector. The Kalman filter is initialized by setting $\hat{\theta}(0) = 0$ and $P(0) = \delta I$, where I is a identity matrix.

D. Hybrid Force/Motion Control

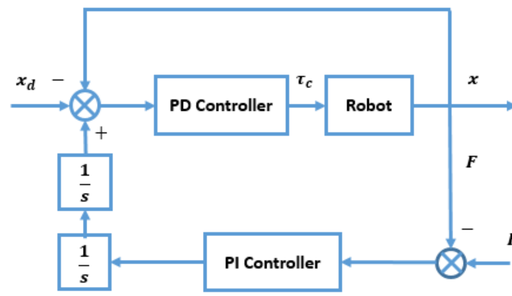

Fig. 3. Block diagram of the hybrid force/motion controller.

In order to reproduce the contact force profile, a hybrid force/motion controller is developed, which is shown in Fig. 3. The original controller of the Baxter includes a position controller and a PD controller with gravity compensation. This controller is stable and is easy to use. Therefore, we implement the hybrid force/motion controller based on it, simply adding a outer force control loop on the original control loop. As shown in Fig. 3, the error between the actual contact force and the desired force is taken as the input of the PI controller, then the output of the PI controller is double integrated, transformed into the same unit of position. Finally, this signal is used to compensate for the position. This newly developed controller is easy to implemented and won't destroy the stability of the original position controller.

IV. Experiment

A. Experimental Setup

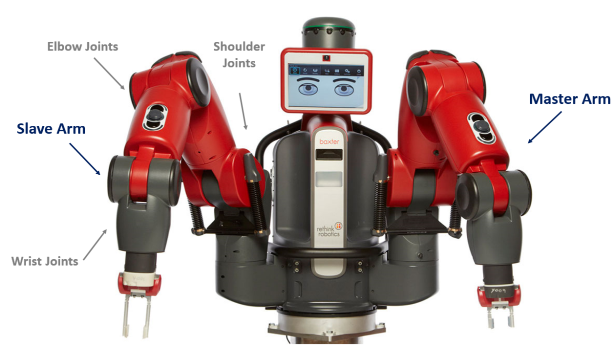

Fig. 4. The Baxter robot.

In this paper, the Baxter robot (Fig. 4) built by Rethink Robotics is employed to verify the proposed framework. The Baxter robot is a dual-arm robot that has seven joints in each arm, including two joints in the shoulder, two joints in the elbow and three joints in the wrist. It provides the Python application programming interface (API) for users to easily program and use. The Baxter is equipped with various sensors, e.g., position sensor, camera in its head, etc. However, it isn't equipped with any force sensor and its force measurement API is implemented by computing the inverse dynamics model, which is usually inaccurate and subject to relatively large error. Besides, adding a force sensor will increase the system complexity and cost. Therefore, in this paper, the momentum-based force observer is applied as an alternative solution.

The Baxter robot has three control modes: torque control mode, velocity control mode and position control mode. Under the position control mode, a PD controller with gravity compensation is activated to achieve stable control. Our hybrid force/motion control framework is implemented based on the position control mode. Extra input computing by a PI controller is added to the original position control input to achieve force reproduction.

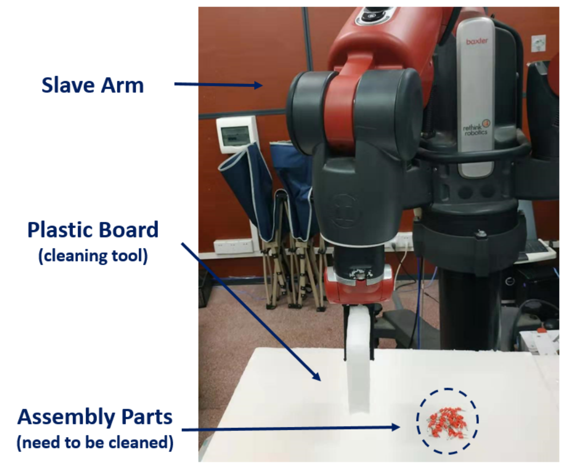

Fig. 6. The setup of the cleaning task experiment: a soft plastic board is clamped on the gripper of the slave arm, which serves as the cleaning tool. The Baxter robot is expected to clean the assembly parts off the table on the left hand side.

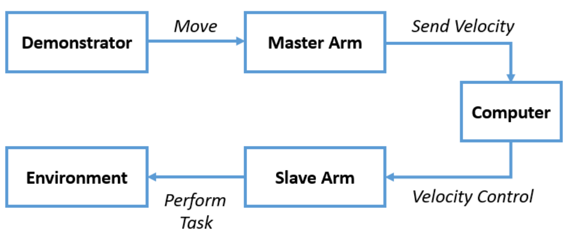

Fig. 5. The master-slave control mode.

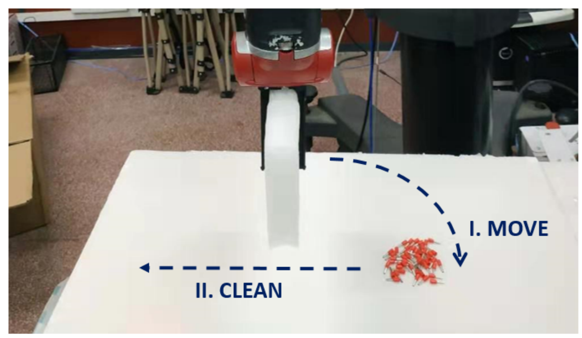

Fig. 7. The conduction of the cleaning task, composed of a 'MOVE' motion and a 'CLEAN' motion.

The experiment includes the demonstration phase, the modelling and skill generalization phase and the skill reproduction phase. In the demonstration phase, the robot is operated in the G-Zero mode of the Baxter robot, which enables users to demonstrate a motion task by directly moving the arm of robot. Considering that the motion of robot arm will affect the performance of the force observer, the arm-moving and the running of force observer are therefore undertaken on different robot arms. Thus, the master-slave control mode is taken in the demonstration phase. The left arm of the Baxter robot serves as master arm and the right arm as slave arm (see Fig. 4). The demonstrator moves the master arm to demonstrate, and the velocities of each joint of the master arm are applied to control the motion of the slave arm, i.e., the task is actually performed by the slave arm, as shown in Fig. 5. The motion trajectories of the slave arm are recorded and meanwhile the force observer is used to estimate the contact force between the slave arm and the environment. Then the recorded trajectories and force are modelled by DMPs simultaneously for the purpose of skills transfer.

B. Robot Learning Task – Table Cleaning

A cleaning task is carried out in our experiment to verify the proposed skill transfer framework. As shown in Fig. 6, a soft plastic board is clamped on the gripper of the slave arm, which serves as the cleaning tool. The Baxter robot is expected to clean the assembly parts off the table. To perform this task, the Baxter robot need to move its slave arm to the right hand side of the assembly parts (called the 'MOVE' motion), and then push the parts off the table from the left hand side (called the 'CLEAN' motion). The process is illustrated by Fig. 7.

The demonstration of the cleaning task is performed under the master-slave mode as mentioned in Section IV-A. In this process, the motion of the end-effector of the slave arm is recorded. Meanwhile, in the 'CLEAN' phase, the momentum-based force observer is used to estimate the contact force between the end-effector and the table, and the Kalman filter is applied to smooth the estimate. Fig. 8 displays the force measured with sensor, the estimated force and the smoothed curve after Kalman filtering. It is found that the contact force rises at first when the end-effector presses the table and moves, and then goes down when the end-effector is going to leave the table. On the other hand, the difference between the measured force by the observer and the estimated force by a force sensor is viewed as the error of estimation. However, it is found in Fig. 8 that the error is relatively small.

In the reproduction phase, we first design a set of comparative experiments to confirm the effectiveness of the hybrid force/motion control method. In the first experiment, the demonstration is directly reproduced by the position control mode, without exploiting the estimated contact force. In the second experiment, the hybrid force/motion controller is employed to reproduce the motion and the contact force as well. Fig. 9 illustrates the experimental outcomes. It is seen that the robot fails to perform the cleaning task under the position control only mode because the contact force is not large enough to avoid any leakage of the small parts during the CLEAN phase. While, in the hybrid force/motion control mode, the robot can successfully perform the task as demonstrated.

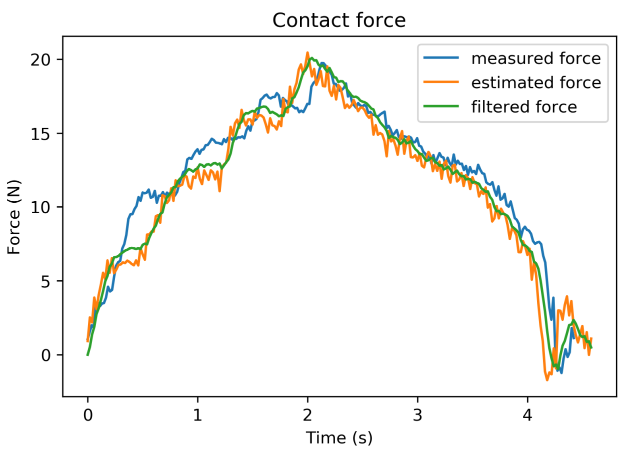

Fig. 8. Contact force between the end-effector and the table in the CLEAN phase.

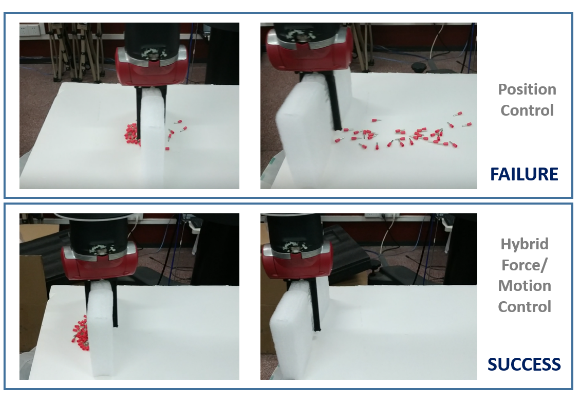

Fig. 9. Experimental results of the comparative experiments: the robot fails to perform the cleaning task by taking the position control only mode; and then successfully conduct the task by involving the contact force information in robot control.

C. Generalization

We then consider a new situation to verify the motion and force generalization. In particular, we change the location of the particle parts to a new place as shown in Fig. 10. In this case, the motion trajectory need to be rescheduled. As described in Section III-B, two DMPs models are built to deliver the MOVE motion and the CLEAN motion in a demonstrated task, respectively. The parameters α and β are set to 120 and 20, respectively. The number of basis functions is chosen as 90. The least squares method is used to learn the weight parameters of the DMPs. We then adapt these two models to make them suitable for the new target place of the MOVE and the CLEAN motion. Fig. 11 and Fig. 12 show the performing results accordingly. Note this change of position only takes place in the direction of the y-axis.

If we take the generalized motions and force estimate from the original task to control the robot under the hybrid force/motion control mode, we find that the robot fails to perform the task due to the mismatch between the motion and contact force. This means that the contact force should also be generalization. Therefore, we adjust the DMPs model for the contact force by increasing the force amplitude with a similar approach for the motion. The parameters α and β of the DMPs are set to 150 and 25 in this case, respectively. The number of basis functions is increased to 100. Fig. 13 displays the contact forces before and after the generalization. By taking these generalized motions and force into the hybrid force/motion controller we employ, the robot can finally perform the task with success.

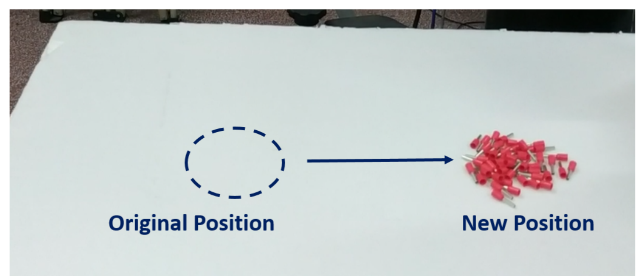

Fig. 10. New task situation: the location of the parts is changed.

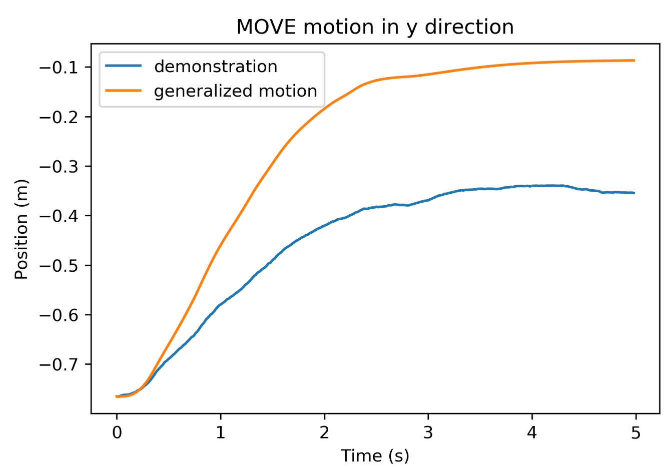

Fig. 11. Generalization of the MOVE motion.

V. Conclusion

Future autonomous robots or cognitive agents in complex systems need to produce a more efficient human-robot col-

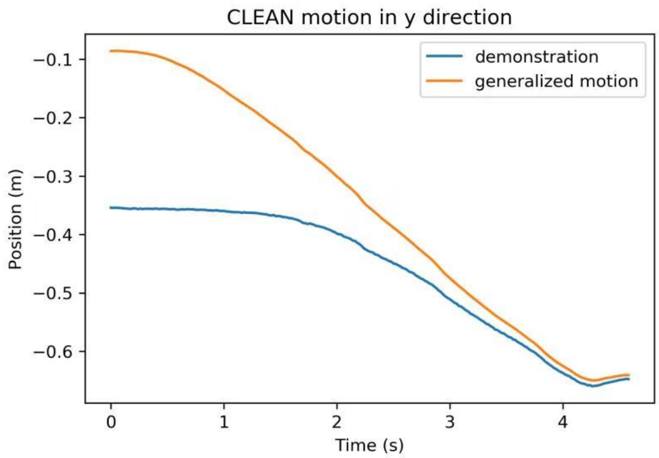

Fig. 12. Generalization of CLEAN motion.

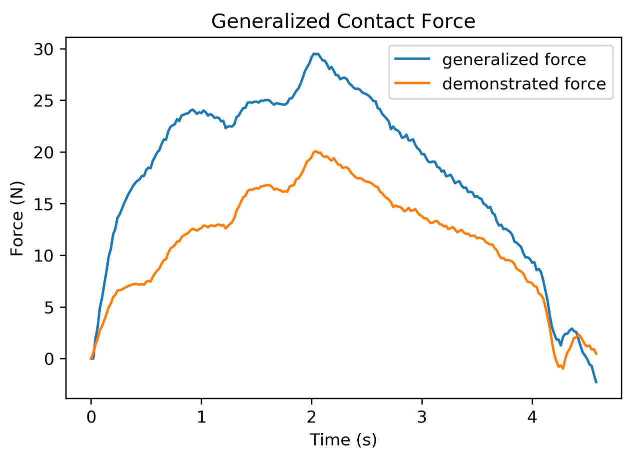

Fig. 13. Generalization of contact force.

laboration to increase technical autonomy, enhance safety, favour more productive human labour and provide better services to the public. This can be achieved by making human-robot interaction more intuitive by adopting techniques like imitation learning, mimicking the way humans teach and learn to themselves. This will reduce the cognitive workload of the users and increase acceptability and usability of cognitive systems and robots. This paper has proposed a novel cognitive learning framework for human-robot skill transfer, which simultaneously considers the motion and the contact force during the demonstration. The DMPs are built to model the motion and the force to achieve skill generalization. To avoid increasing the system complexity, a momentum-based force observer is taken to estimate the contact force, without adding any extra force sensors. To reproduce the motion and the contact force, the hybrid force/motion controller is developed based on the original position controller of the Baxter robot. Experiments with the Baxter Robot have verified that the robot can perform the force-related task better than the motion-only method by employing the proposed robot learning framework. The success rate of task performing is also improved. In the future, to increase acceptability and usability of the proposed approach, we will consider involving other skills, e.g., stiffness profiles of the human user into the framework, and also developing better control scheme to achieve more accurate force tracking.

REFERENCES

[1] M. J. Matarić, "Socially assistive robotics: Human augmentation versus automation," *Science Robotics*, vol. 2, no. 4, p. eaam5410, mar 2017.

[2] N. Wang, A. D. Nuovo, A. Cangelosi, and R. Jones, "Temporal patterns in multi-modal social interaction between elderly users and service robot," *Interaction Studies*, vol. 20, no. 1, pp. 4–24, 2019.

[3] A. Di Nuovo, D. Conti, G. Trubia, S. Buono, and S. Di Nuovo, "Deep learning systems for estimating visual attention in robot-assisted therapy of children with autism and intellectual disability," *Robotics*, vol. 7, no. 2, p. 25, 2018.

[4] P. Liang, C. Yang, N. Wang, Z. Li, R. Li, and E. Burdet, "Implementation and test of human-operated and human-like adaptive impedance controls on baxter robot," in *TAROS 2014: Advances in Autonomous Robotics Systems*, 2014, pp. 109–119.

[5] Y. Li, K. P. Tee, R. Yan, W. L. Chan, Y. Wu, and D. K. Limbu, "Adaptive optimal control for coordination in physical human-robot interaction," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2015, pp. 20–25.

[6] C. Yang, C. Zeng, Y. Cong, N. Wang, and M. Wang, "A learning framework of adaptive manipulative skills from human to robot," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 2, pp. 1153–1161, 2018.

[7] E. A. Kirchner, J. de Gea Fernandez, P. Kampmann, M. Schröer, J. H. Metzen, and F. Kirchner, "Intuitive interaction with robots – technical approaches and challenges," in *Formal Modeling and Verification of Cyber-Physical Systems*. Springer Fachmedien Wiesbaden, 2015, pp. 224–248.

[8] M. S. Prewett, R. C. Johnson, K. N. Saboe, L. R. Elliott, and M. D. Coovert, "Managing workload in human–robot interaction: A review of empirical studies," *Computers in Human Behavior*, vol. 26, no. 5, pp. 840–856, sep 2010.

[9] A. Moniz and B.-J. Krings, "Robots working with humans or humans working with robots? searching for social dimensions in new human-robot interaction in industry," *Societies*, vol. 6, no. 3, p. 23, aug 2016.

[10] A. Sciutti, M. Mara, V. Tagliasco, and G. Sandini, "Humanizing human-robot interaction: On the importance of mutual understanding," *IEEE Technology and Society Magazine*, vol. 37, no. 1, pp. 22–29, mar 2018.

[11] B. D. Argall, S. Chernova, M. Veloso, and B. Browning, "A survey of robot learning from demonstration," *Robotics and autonomous systems*, vol. 57, no. 5, pp. 469–483, 2009.

[12] S. Schaal, "Is imitation learning the route to humanoid robots?" *Trends Cognitive Sci.*, vol. 3, no. 6, pp. 233–242, 1999.

[13] S. Calinon, D. Bruno, M. S. Malekzadeh, T. Nanayakkara, and D. G. Caldwell, "Human–robot skills transfer interfaces for a flexible surgical robot," *Computer methods and programs in biomedicine*, vol. 116, no. 2, pp. 81–96, 2014.

[14] J. Hu, Z. Yang, Z. Wang, X. Wu, and Y. Ou, "Neural learning of stable dynamical systems based on extreme learning machine," in *Information and Automation, 2015 IEEE International Conference on*. IEEE, 2015, pp. 306–311.

[15] X. Yin and Q. Chen, "Learning nonlinear dynamical system for movement primitives," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, 2014, pp. 3761–3766.

[16] A. J. Ijspeert, J. Nakanishi, H. Hoffmann, P. Pastor, and S. Schaal, "Dynamical movement primitives: learning attractor models for motor behaviors," *Neural Comput.*, vol. 25, no. 2, pp. 328–373, 2013.

[17] S. Calinon, Z. Li, T. Alizadeh, N. G. Tsagarakis, and D. G. Caldwell, "Statistical dynamical systems for skills acquisition in humanoids," in *Proc. IEEE-RAS Int. Conf. Humanoid Robots*, 2012, pp. 323–329.

[18] S. Calinon and A. Billard, "Statistical learning by imitation of competing constraints in joint space and task space," *Adv. Robot.*, vol. 23, no. 15, pp. 2059–2076, 2009.

[19] S. Calinon, F. Guenter, and A. Billard, "On learning, representing, and generalizing a task in a humanoid robot," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 37, no. 2, pp. 286–298, 2007.

[20] K. Mülling, J. Kober, O. Kroemer, and J. Peters, "Learning to select and generalize striking movements in robot table tennis," *Int. J. Robot. Res.*, vol. 32, no. 3, pp. 263–279, 2013.

[21] P. Pastor, H. Hoffmann, T. Asfour, and S. Schaal, "Learning and generalization of motor skills by learning from demonstration," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2009, pp. 763–768.

[22] C. Yang, C. Zeng, C. Fang, W. He, and Z. Li, "A dmps-based framework for robot learning and generalization of humanlike variable impedance skills," *IEEE/ASME Transactions on Mechatronics*, vol. 23, no. 3, pp. 1193–1203, 2018.

[23] S. Haddadin, A. De Luca, and A. Albu-Schäffer, "Robot collisions: A survey on detection, isolation, and identification," vol. 33, no. 6, pp. 1292–1312, 2017.

[24] P. K. Pook and D. H. Ballard, "Recognizing teleoperated manipulations," in *[1993] Proceedings IEEE International Conference on Robotics and Automation*. IEEE, 1993, pp. 578–585.

[25] J. D. Sweeney and R. Grupen, "A model of shared grasp affordances from demonstration," in *2007 7th IEEE-RAS International Conference on Humanoid Robots*. IEEE, 2007, pp. 27–35.

[26] M. N. Nicolescu and M. J. Mataric, "Experience-based representation construction: learning from human and robot teachers," in *Proceedings 2001 IEEE/RSJ International Conference on Intelligent Robots and Systems. Expanding the Societal Role of Robotics in the the Next Millennium (Cat. No. 01CH37180)*, vol. 2. IEEE, 2001, pp. 740–745.

[27] S. Schaal, A. Ijspeert, and A. Billard, "Computational approaches to motor learning by imitation," *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, vol. 358, no. 1431, pp. 537–547, 2003.

[28] Y. Wu and Y. Demiris, "Towards one shot learning by imitation for humanoid robots," in *2010 IEEE International Conference on Robotics and Automation*. IEEE, 2010, pp. 2889–2894.

[29] Y. Wu, Y. Su, and Y. Demiris, "A morphable template framework for robot learning by demonstration: Integrating one-shot and incremental learning approaches," *Robotics and Autonomous Systems*, vol. 62, no. 10, pp. 1517–1530, 2014.

[30] S. Chernova and M. Veloso, "Confidence-based policy learning from demonstration using gaussian mixture models," in *Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems*. ACM, 2007, p. 233.

[31] C. Sammut, S. Hurst, D. Kedzier, and D. Michie, "Learning to fly," in *Machine Learning Proceedings 1992*. Elsevier, 1992, pp. 385–393.

[32] T. I. M. I. H. Inoue, M. Inamura, and H. Inaba, "Acquisition of probabilistic behavior decision model based on the interactive teaching method," in *Proceedings of the Ninth International Conference on Advanced Robotics, ICAR99*, 1999.

[33] J. Saunders, C. L. Nehaniv, and K. Dautenhahn, "Teaching robots by moulding behavior and scaffolding the environment," in *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction*. ACM, 2006, pp. 118–125.

[34] S. Vijayakumar and S. Schaal, "Locally weighted projection regression: An o (n) algorithm for incremental real time learning in high dimensional space," in *Proceedings of the Seventeenth International Conference on Machine Learning (ICML 2000)*, vol. 1, 2000, pp. 288–293.

[35] S. Vijayakumar, A. D'souza, and S. Schaal, "Incremental online learning in high dimensions," *Neural Comput.*, vol. 17, no. 12, pp. 2602–2634, 2005.

[36] D. H. Grollman and O. C. Jenkins, "Dogged learning for robots," in *Proceedings 2007 IEEE International Conference on Robotics and Automation*. IEEE, 2007, pp. 2483–2488.

[37] D. C. Bentivegna and C. G. Atkeson, "Learning from observation using primitives," in *Proceedings 2001 ICRA. IEEE International Conference on Robotics and Automation (Cat. No. 01CH37164)*, vol. 2. IEEE, 2001, pp. 1988–1993.

[38] E. Ugur and H. Girgin, "Compliant parametric dynamic movement primitives," *Robotica*, pp. 1–18, 2019.

[39] Y. Wu, R. Wang, L. F. D'Haro, R. E. Banchs, and K. P. Tee, "Multi-modal robot apprenticeship: Imitation learning using linearly decayed dmp+ in a human-robot dialogue system," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2018, pp. 1–7.

[40] R. Wang, Y. Wu, W. L. Chan, and K. P. Tee, "Dynamic movement primitives plus: For enhanced reproduction quality and efficient trajectory modification using truncated kernels and local biases," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2016, pp. 3765–3771.

[41] F. Stulp, E. A. Theodorou, and S. Schaal, "Reinforcement learning with sequences of motion primitives for robust manipulation," *IEEE Transactions on robotics*, vol. 28, no. 6, pp. 1360–1370, 2012.

[42] A. Gams, M. Do, A. Ude, T. Asfour, and R. Dillmann, "On-line periodic movement and force-profile learning for adaptation to new surfaces," in *2010 10th IEEE-RAS International Conference on Humanoid Robots*. IEEE, 2010, pp. 560–565.

[43] M. Kalakrishnan, L. Righetti, P. Pastor, and S. Schaal, "Learning force control policies for compliant manipulation," in *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2011, pp. 4639–4644.

[44] A. De Luca, D. Schroder, and M. Thummel, "An acceleration-based state observer for robot manipulators with elastic joints," in *Proceedings 2007 IEEE international conference on robotics and automation*. IEEE, 2007, pp. 3817–3823.

[45] S. Haddadin, *Towards safe robots: approaching Asimov's 1st law*. Springer, 2013, vol. 90.

[46] A. De Luca and R. Mattone, "Sensorless robot collision detection and hybrid force/motion control," in *Proceedings of the 2005 IEEE international conference on robotics and automation*. IEEE, 2005, pp. 999–1004.

[47] A. De Luca, A. Albu-Schaffer, S. Haddadin, and G. Hirzinger, "Collision detection and safe reaction with the dlr-iii lightweight manipulator arm," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2006, pp. 1623–1630.

[48] F. L. Lewis, L. Xie, and D. Popa, *Optimal and robust estimation: with an introduction to stochastic control theory*. CRC press, 2017.