Teaching Robots to Grasp Like Humans: An Interactive Approach

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Abstract—This work investigates how the intricate task of grasping may be learned from humans based on demonstrations and corrections. Due to the complexity of the task, these demonstrations are often slow and even slightly flawed, particularly at moments when multiple aspects (i.e., end-effector movement, orientation, and gripper width) have to be demonstrated at once. Rather than training a person to provide better demonstrations, non-expert users are provided with the ability to interactively modify the dynamics of their initial demonstration through teleoperated corrective feedback. This in turn allows them to teach motions outside of their own physical capabilities. In the end, the goal is to obtain a faster but reliable execution of the task. The presented framework learns the desired movement dynamics based on the current Cartesian position with Gaussian Processes (GP), resulting in a reactive, time-invariant policy. Using GPs also allows online interactive corrections and active disturbance rejection through epistemic uncertainty minimization. The experimental evaluation of the framework is carried out on a Franka-Emika Panda. Tests were performed to determine i) the framework’s effectiveness in successfully learning how to quickly grasp an object, ii) ease of policy correction to environmental changes (i.e., different object shapes and mass), and iii) the framework’s usability for non-expert users.

I. INTRODUCTION

More often than not, robots employ a grasping strategy wherein they approach the object, stop and grasp it and only then resume moving. The standard approach to robot grasping consist in two phases: approach the object and then perform the gripper actuation until success. We as humans, on the other hand, tend to grasp things in a single fluent and quick motion. Of course, robots should also be able to complete a task fairly quickly, which in the case of grasping introduces a number of challenges, both from a control point of view [1] as well as a learning point of view [2].

Learning from Demonstration (LfD) has become a popular approach for allowing non-expert users to teach robots and thus more easily integrate them into the working and daily environment [3]. Yet these provided demonstrations are sub-optimal compared to what the robot might be able to achieve. This can lead to a reduced efficiency and utility of executing a task with a robot, despite the advantage that robots are able to preform tasks more reliably and for longer periods of time than people. However, if we consider how people learn skills, they first learn to perform a task slowly and correctly, and only once they are confident do they speed up the execution so as not to compromise on the success of the task. This strategy can also be applied to robot learning.

At the same time, it is important to consider that often, the execution of a task cannot be sped up uniformly. For example, when learning a grasping movement, retaining a high velocity when approaching the object can generate high impact forces which can cause the object to bounce away or topple over, potentially damaging the item in question as well as making it impossible to grasp on time. We as people are able to identify such constraints and adapt accordingly, and can transfer this knowledge to the robot through demonstration.

The presented framework continues the study on inter-
active learning of complex robot motion using Gaussian Process (GP) regression, recently introduced in ILoSA [4] for learning manipulation tasks. In the prior work, we introduced the minimisation of the epistemic uncertainty, which can be derived directly from the GP models. This provides an elegant solution to covariate shift, avoiding dangerous extrapolation which is particularly important when performing high speed motions. The previous work focused on learning a variable impedance controller for stable force tasks and it limited the achievable robot velocity to ensure safety in the case of contact loss. Nonetheless, higher velocities may be desired, even if these could not be physically demonstrated. The work we introduce here focuses attention on interactively learning robot motion dynamics such that they can be shaped through different types of corrections. Additionally, this work also introduces the learning of both orientation and gripper control to learn more complex grasping behaviour.

Fig. [1] summarizes the three phases of learning in the teaching of a re-shelving operation: the initialization of the policy with kinesthetic demonstration, the shaping of the dynamics with teleoperated corrections and the final supervision of good learning in the autonomous task execution. This use-case brings with it the challenge that it requires precision both when approaching the object and when placing it, and also needs to consider a gentle handling of the object.

To summarize, the contribution of this work are on the interactive learning of robot motion dynamics in accordance to the user’s desires for a fast-paced task such as grasping. Furthermore, we verify the feasibility of this approach with non-expert users where the interactive corrections allow to shape a non-zero-velocity but successful object grasping.

II. BACKGROUND AND RELATED WORK

When executing high-speed manipulation tasks which involve establishing contact with an object, it is important to consider the behaviour around the moment of impact. A reoccurring approach observed in existing works consists of adapting the relative velocity in order to mitigate the effects of the impact [5], [6]. Another strategy which has been employed to absorb impacts particularly in catching tasks, involves utilising a follow-through behaviour which continues to track the predicted path of an object even after interception [6], [7]. A follow-through behaviour, however, is not applicable to stationary objects. A similar behaviour can nevertheless be obtained by employing a variable impedance controller with low stiffness. Indications of the benefits of impedance control for absorbing impacts could be observed in other contact tasks such as quadrupedal trotting [8], and learning a hopping movement on a floating base system [9].

Unlike many other controllers, impedance control has the capability of incorporating a compliant behaviour into a provided attractor. This is achieved by modelling the desired robot dynamics in the form of a mass-spring-damper system. Depending on the defined system properties for inertia Λ, damping D and stiffness K_s, the dynamics of the end-effector in the case of Cartesian impedance are given through the following relation

$$\Lambda(q)\ddot{x} = K_s\Delta x - D\dot{x} + f_{ext},$$

with $f_{ext}$ representing the force at the end-effector where the gravitational and Coriolis terms have been pre-compensated. Considering this relation, it is possible to induce a compliant behaviour which allows a softer interaction with the grasped object and stable motions with critical damping.

An impedance controller, however, is unable to mitigate the initial impact force irrespective of the set stiffness as demonstrated in [10]. This is because the main contribution to the impact force is the velocity of the impacting objects. The results presented in [10] do, however, strengthen the observation that the increased compliance provided by impedance is beneficial for absorbing the post-impact forces. While matching the velocity of an object likely achieves the best reduction of impact force, such an approach may not be optimal when considering the total time of the trajectory execution. This is especially true for the case of a static object, wherein matching velocities would effectively bring the robot to stand-still prior to the grasping action. A better approach, therefore, is to interactively learned the feasible non-zero contact velocity while ensuring moderate impact forces.

A. Learning Dynamic Movements

Being able to adapt/correct the learned velocity with ease plays a key role in speeding up the overall execution of the demonstrated trajectory while also considering that the movement dynamics may require different degrees of adaptation at different points of the trajectory; for example partly slowing down prior to the moment of interception. Different works explore speed adaptation during trajectory execution using different function approximators. One approach involves altering the phase rate of probabilistic movement primitives (ProMPs) [11], [12], whereas another proposes the use of a modified version of Dynamical Movement Primitives (DMPs) in which the speed is altered through an additional phase-dependent temporal scaling factor [5], [13]. While the focus of these existing works is in combining imitation learning with reinforcement learning, our approach combines imitation learning and human interactive corrections [14].

An alternative to DMPs is Gaussian-based regression such as Gaussian Mixture Regression (GMR) or Gaussian Processes (GP) [15]. GMR, in particular, has been utilised in works investigating the catching of objects [7], [16], which is closely related to grasping objects quickly. These approaches utilise GMMs to model a stable motion towards the goal [17] and for learning the desired hand orientation [7]. Also, GPs have been used for shaping a motion from human demonstrations, through the local modification of a stable field [18]. However, not one of these methods propose to use the minimization of uncertainty as a stabilization criteria, nor develops a data-efficient interactive correction of the policy.

Furthermore, our proposed framework aims to study the teaching feasibility of this highly dynamic task through
Learning from Demonstration in order to allow even non-expert users to program the robot’s motions. While it may not be possible to demonstrate the desired motion dynamics, the aim is to overcome this limitation through the online correction of the learned policy. To our knowledge, there is no study about the learning of non-zero-velocity grasping policy using only a learned reactive controller shaped from online human corrections.

III. METHODOLOGY

The goal of this framework is to enable a user to teach the robot the desired motion through demonstration and correction, see Alg. III-A. The robot is learning the desired minimum uncertainty dynamical system on the end-effector, formalized in Sec. III-A and the dynamics of the gripper orientation and width as a direct mapping to the current robot position, formalized in Sec. III-B. The main aim is to show that it is possible to learn a policy and later correct the velocity so as to achieve and surpass the performance of a skilled demonstrator. All of these aspects are modelled with Gaussian Processes, allowing interactive corrections of the dynamics and actions online, see Sec. III-C.

A. Learning a Minimum Uncertainty Dynamical System

A non-linear dynamical system can be described by

$$\dot{x} = f(x)$$

where \(x\) is the robot state and \(f\) identifies the transition of the robot state. This type of formulation would fit perfectly in a velocity controller, however, due to the necessity of dealing with impacts, for which an impedance controller is more suitable [8, 9], we can reformulate the motion dynamics with its integral form, i.e. we are controlling the desired next point of the motion and not the current desired velocity, according to

$$x_{\text{des}} = x_t + \int_{t}^{t+\Delta t} \dot{x} \, dt = x_t + (x_{t+\Delta t} - x_t) = x_t + \Delta x(x_t)$$

where \(x_{\text{des}}\) is the desired attractor position. Since \(\dot{x}\) is a function of the current position \(x\), the integral attractor distance \(\Delta x\) is going to be a function of the robot position \(x_t\). The dynamical system can be seen as an external (and slower) control loop where the attractor position is updated as a function of the robot position while the inner (and faster) control loop simulates the dynamics of a critically damped second order dynamical system described by Eq. (?). As an analogy to humans, the slower loop can be seen as the intention update of the human when generating their motion according to the current arm position while the impedance control represents the compliance of the muscles and the joints in the interaction with the environment.

The desired \(\Delta x\) is fitted with a Gaussian Process (GP) using the data of a kinesthetic demonstration and user-provided corrections. A GP is a non-parametric regression method [15] where the mean and variance of the evaluation point are denoted as

$$\mu = k_*(\xi, x)^\top (K(\xi, \xi) + \sigma_n^2 I)^{-1} y,$$

$$\Sigma = k(x, x) - k_*(\xi, x)^\top (K(\xi, \xi) + \sigma_n^2 I)^{-1} k_*(\xi, x),$$

where \(x\) is the evaluation point, \(\xi\) is the input database and \(y\) is the output database, and \(\mu\) and \(\Sigma\) are the mean and variance of the regression in the evaluation point. The chosen kernel of the process in this study is the Automatic Relevance Determination Squared Exponential kernel

$$k(x_i, x_j) = \sigma_f^2 e^{-\frac{1}{2}(f(x_i) - f(x_j))^\top \Theta (f(x_i) - f(x_j))}$$

used for evaluating the correlation of the queried point with itself \(k(x, x)\) and with the point of the database \(k_*(\xi, x)\) but also for the computation of the covariance matrix \(K(\xi, \xi)\) of the \(n\)-dimensional Gaussian distribution where the \(n\) outputs \(y\) are supposed to be sampled from. The matrix \(\Theta\) is diagonal and its value (along with the process noise \(\sigma_n\)) are optimized as likelihood maximization of the sampling of the \(y\) from the fitted GP. Additionally, we employed a constrained optimization, in order to have a feasible set of hyper-parameters to explore, avoiding overfitting or underfitting.

Finally, something to consider when learning a dynamical system in a reactive formulation is that the next robot position is a function of the learned desired transition but also the external disturbances. This may lead the robot in a position where its policy is not confident anymore, i.e., high epistemic uncertainty. Depending on where this might occur, the robot may not be able to successfully grasp the object or bring it to its goal and execute its motion. When we, as humans, execute a motion we try to remain in regions where we are confident about what we have learned up to that point. To encode this behaviour also in the robot, the dynamical system was superposed with another dynamical system that brings the robot towards regions of low uncertainty. From a control point of view, this results in adding another attractor field that is proportional to the gradient of the variance of the regression in the evaluation point. The chosen field is

$$\Delta x_{\text{stable}}(x) = -\alpha \nabla \Sigma = \alpha \left(2k_*(\xi, x) + \sigma_n^2 I\right)^{-1} \frac{\partial k_*(\xi, x)}{\partial x},$$

where \(x\) is the evaluation point, and \(\alpha\) is an automatically modulated constant according to a maximum allowed attractor distance, which ensures that \(\Delta x_s\) is never higher than a set threshold. This repulsive field can be seen as a behavioural stiffness: considering a variance manifold as a potential energy, similar to elasticity, the robot is always acting towards the minimization of this quantity; similarly, the lower level control, “the muscles”, is trying to converge to the goal in order to minimize the tension, i.e., the elastic energy. Thus, the Minimum Uncertainty Dynamical System (MUDS) can be summarized as

$$x_{\text{des}} = x + \Delta x(x) - \alpha \nabla \Sigma(x).$$

This approach is effective due to two factors. The first is that as the evaluation point moves further from the known region, the inference is not correlated anymore with the demonstration data. In turn, the predictions begin to vanish towards the mean of the Gaussian Process, which is set to zero. Simultaneously, the variance begins to increase and
Algorithm 1: Teaching Framework

1. **a) Kinesthetic Demonstration(s)**
2. **while Trajectory Recording do**
3. \( \Delta x_{\text{dem}}(x_{t-1}) = x_t - x_{t-1} \)
5. **end**
6. **Train(GPs)**
7. **b) Interactive Corrections**
8. **Data:** \( \Delta x_{\text{dem}}, \gamma_{\text{dem}}, \sin \theta_{\text{dem}}, \cos \theta_{\text{dem}}, w_{\text{dem}} \)
9. **while Control Active do**
10. \( \text{Receive}(x) \)
11. **if Received Human feedback \( \Delta x^e, \gamma^e, w^e \) then**
12. \( \text{Correct}(\Delta x^e \rightarrow \Delta x_{\text{dem}}, \gamma^e \rightarrow \gamma_{\text{dem}}, w^e \rightarrow w_{\text{dem}}) \)
13. **end**
14. \( [\Delta x, \Sigma] = \text{GP}_{\Delta x}(x) \)
15. \( \gamma = \text{GP}_{\gamma}(x) \)
16. \( w_{\text{des}} = \text{GP}_{MU}(x) \)
17. \( [\sin(\theta), \cos(\theta)] = \text{GP}_{\theta}^{MU}(x) \)
18. \( \theta_{\text{des}} = \arctan2(\sin(\theta), \cos(\theta)) \)
19. \( x_{\text{des}} = x + \gamma \Delta x - \alpha \nabla \Sigma \)
20. **Send\( (x_{\text{des}}, \theta_{\text{des}}, w_{\text{des}}) \)**
21. **end**

B. Learning Minimum Uncertainty Mappings

When learning a complex task like grasping, the dynamics of the end-effector position must be augmented with the dynamics of the gripper orientation and width. Because in a trajectory, the dynamics of the orientation and gripper are coupled with the dynamics of the end-effector, we decided to learn the controlled action as a function of the robot’s position with a GP. However, if the predictions are done based on the current position, when outside of the region of uncertainty, the robot would output the mean of an independent Process (i.e., zero radians for the orientation along all three axes and maximum gripper width) which could lead to an undesirable generalization, e.g., tilting or dropping objects. In order to solve this problem, we propose a minimum uncertainty kernel where the new correlation function is obtained as

\[
 k_{MU}(x_i, x_j) = \sigma_f^2 e^{-\frac{1}{2} (g(x_i) - x_j)^T \Theta (g(x_i) - x_j)},
\]

with \( g(x) = \arg\max_{\xi} (k(\xi, x)) \).

where \( k \) is the Radial Basis Function (RBF) kernel fitted on the data. This new prediction can be interpreted as a “mental” projection on the point of maximum correlation according to the standard RBF kernel used for the main GP. The aim is to explicitly avoid extrapolating outside the original demonstrated data while still using the property of a smooth regressor of the GP. This behaviour also matches the philosophy of actively taking actions that would always minimize the uncertainty on the current robot state. When the evaluation of the Gaussian Process is performed with this minimum uncertainty rule, we denote them with the superscript \( MU \).

In order to fit the desired angles with a regressor, it was necessary to have a smooth and continuous representation of the angles. To this end we fit both \( \sin(\theta) \) and \( \cos(\theta) \) transformations of the Euler angles and convert them back after online inference during robot control (l. 17 Alg. [1]).

C. Interactive Policy Correction with Human-in-the-Loop

After learning from kinesthetic demonstrations the desired transition \( \Delta x \), angle \( \theta \) and the gripper width \( w \) in the different points of the recorded trajectory, we still need to allow the user to correct the policy during the robot execution. Considering that the goal is to speed up the motion, it is not safe anymore to use a direct kinesthetic feedback for shaping the policy. Similarly when a teacher is correcting the movements of an apprentice, they are giving corrective feedback on the desired movement and the local velocity. Thus, due to the necessity of modifying the magnitude of the attractor distance proportionally in all directions (when higher/lower velocity are requested), a scalar factor is learned as a function of the position, resulting in a desired attractor

\[
 x_{\text{des}} = x + f(x) = x + \gamma(x) \Delta x - \alpha \nabla \Sigma\]

where \( \gamma(x) \) is the the attractor scaling factor.

With this formulation, corrections can be allocated in the 3 different components of the vector or on the total magnitude of the vector itself. Furthermore, the evaluation of the kernel allows the corrective input to be smoothly spread to surrounding data points in accordance to their correlation.

The update rule was thus chosen as

\[
y^\text{demo} = y^\text{demo} + k^*_{\gamma} (\xi, x) \epsilon_{\mu}
\]

where \( k^*_{\gamma} \) is the correlation vector \( k_{\gamma} \), normalised such that \( \sigma_f = 1 \), and \( \epsilon_{\mu} \) is the given correction provided at \( x \).

This rule was applied for correcting the attractor distance \( \Delta x \), scalar factor \( \gamma \) and the width of the gripper prongs \( w \). It has previously been shown that spreading the corrections on the database is more user-friendly, as well as time and data efficient [4] than a simpler data aggregation [19], since otherwise the GP model would essentially average between the different outputs for a given input, leading to a slow learning. Additionally, this constraint of spreading the corrections only on existing points of the database avoids to modify the shape of the variance manifold, keeping the motion always close to the kinesthetic demonstration, according to Eq. (21), while still shaping the motion dynamics, encoded in \( \gamma(x) \Delta x(x) \).

IV. VALIDATION EXPERIMENTS

Different experiments were carried out to evaluate the effectiveness, usability as well as robustness of the method. Firstly, the framework’s base functionality of taking slow
demonstrations and allowing the correction of the dynamics through corrective feedback is tested. A second experiment analyses how well a learned policy can accommodate changes in object properties such as size and weight. Lastly, a user validation study was carried out with non-experts in order to establish the usability of the proposed method. A video of the learning and execution of the tasks can be found attached to this paper.

A. Robot Setup

For our experiments we utilise the 7 DoF Franka-Emika Panda with an impedance controller and a ROS communication network for the online control of the robot with a frequency of 100 Hz. Control of the robot's movement was carried out in real-time, whereas the control of the gripper could not be carried out in real-time due to the internal communication protocol. Furthermore, in order to avoid overloading the Gaussian Process with superfluous data, the recording of the trajectory is carried out at 10 Hz considering that whatever the human is showing at higher frequency is noise that would anyway be filtered out by the GP fitting and the impedance policy.

A wireless Logitech Gamepad was used for teleoperated corrections due to the number of required inputs. Due to the limited number of reliable, continuous inputs, both the gripper and scaling factor corrections are provided through discrete increments. The attractor corrections are provided through the continuous inputs of the two thumbsticks, with the movement in the x-y-plane regulated by the left thumbstick and the height regulated by the right thumbstick. As an added safety feature, one of the triggers was utilised as a safety button which, when released, ends the execution of the algorithm, halting the robot. Lastly, users can comfortably start the execution from any point along the trajectory as well as bring the robot to the start of the trajectory. As a final remark, it is worth underlining that the capability of correcting the orientation after the demonstration was not enabled due to the limitations of the teleoperation interface, not due to any limitations surrounding the algorithm itself and is thus left to future work.

B. Interactive Fast Grasping with MUDS

For this experiment, a single demonstration was provided wherein the end-effector orientation, gripper width, and attractor distance are obtained and used for initialising the respective GP models. The goal of the task is to reduce the execution time by 4 times compared to the time needed to demonstrate the motion with kinesthetic teaching. We repeated the experiment a total of 5 times.

Within less than three minutes it was possible to fully train the robot to grasp the object in question at the desired performance, four out of five times. Only a fraction of that time was needed for the demonstration and explicit feedback from the human, amounting on average to around 11.8 s and 6.8 s respectively. This points towards primarily needing fine-tuning corrections from the side of the human, which is further supported by time spent giving corrections for each of the three correctable aspects (see Fig. 3). It is worth noting that a correction round refers to an execution of a trajectory with optional user corrections, which can be stopped at any point of the execution and not just at the goal. The time spent correcting the attractor was minimal, as it was only required around the moment when the object is reached. The reason for this is because the human tends to stop at the object during the demonstration in order to avoid knocking it over. In turn, the attractor distance around that point is virtually zero albeit not perfectly zero. Therefore, depending on the demonstration it may happen that this attractor is not pointing in the desired direction. Increasing the magnitude with the scaling factor could thus result in a movement in an unexpected direction. To avoid this, minor corrections to the attractor were provided for ensuring it follows the desired direction. Afterwards only corrections for the gripper and scaling factor are provided. Any time corrections to the scaling factor were provided, obtaining higher velocity, corrections to the gripper had to be provided as well. This was primarily in order to offset the communication delay of the gripper. Once the desired velocity was achieved the final corrections were directed towards fine-tuning the gripper timing. Due to the unreliability of the gripper, despite corrections to the timings, the gripper still sometimes closed at the incorrect moment. Nevertheless, after corrections, an average
success rate of 82% out of 10 autonomous executions of 5 different trained policies (41 successes over 50 executions in total) could still be achieved. For the complete performance details, please refer to Tab. I. During the experiments, it was established that due to the unreliability of the gripper, it was necessary to push the object for a select period of time, as otherwise the desired performance could not be reached. If the time for pushing the object is too short a very slow motion is needed around the moment of grasping the object, otherwise the grasping success drops to random chance, which could be observed in one of the trials.

One of the main concerns when increasing the velocity along a trajectory is diverging from said trajectory, particularly in curves. While the shape of the trajectory did change slightly, thanks to the uncertainty minimisation, divergence from the trajectory could be avoided even when the attractor magnitude was noticeably increased compared to the original demonstration. This can be observed within the attractor vector fields in Fig. 4. This is an important feature of the proposed method, opening an alternative to many methods that are not dealing with covariate shift when they try to generalize. The goal was to show that even if the dynamics of the trajectory are modified, the obtained trajectory is not changing much, resembling the original demonstration. In our opinion, this feature may promise a safer human-robot coexistence and collaboration.

### Interactive Adaptation to New Object Properties

It can be that we want to grasp a different object after having learned a desired grasping behaviour. Rather than demonstrating and retraining the strategy for every new object, or relying on hard-coded rules in order to adapt to these changes in properties, corrections can be used to adapt the learned policy. To evaluate this, a selection of four different kinds of objects was taken (seen in Fig. 5). First the initial policy was trained on a rigid water-bottle with a weight of 250 g, number 1 in Fig. 5. Once a satisfactory policy was achieved, the training object was swapped out for another object. The policy was then executed and corrected if necessary. Corrections were provided until the point that the new object was successfully grasped, after which an evaluation of the performance was performed. Subsequently, a different object was swapped in and the learned policy was reset to the initial policy.

For each new object, the policy could be successfully corrected. For the same object but with a greater weight (number 2) corrections were primarily needed for increasing the velocity around the moment at which the object was grasped. This is due to a larger force needed to move the heavier object at the desired velocity. For the deformable object (number 3) the initial policy carried out the grasping successfully in the first execution, hence it was deemed that no corrections were necessary. During the performance evaluation, however, three rollouts resulted in unsuccessful grasps due to the gripper closing too late. Since this issue had not occurred in the first rollout of the policy, additional corrections were not provided. Nevertheless, this could have been improved through additional corrections to the gripper and minor alterations to the velocity.

Lastly, for the deformable object (number 4) it was necessary to reduce the speed of the motion for a successful grasp. Otherwise the object kept being knocked over upon impact due to its smaller support polygon. Nevertheless, for all three objects with their different properties it was possible to alter the policy within the time needed for training from a new demonstration, or even within less time if the properties were not too different (see Tab. II).

It is important to note that the strategies for the separate
objects are not stored. Retaining this information would require a further form of knowledge representation or policy parametrization, which is outside the scope of this work. This evaluation does, however, show how an existing policy can be corrected to adapt to previously unseen objects, which can be beneficial for gathering knowledge more quickly.

D. Are Humans great teachers? A User Study

Since the aim of the proposed method is to enable people, who may not have a background in robotics and machine learning, to teach a robot, a preliminary user validation study was carried out. A total of ten participants aged 23 to 28 took part in this study (approved by TU Delft Human Research Ethics Committee). The same setup as in Fig. 4 was used, with the bag being replaced by a small square tower to provide a clearer goal point for the participants. Participants were given up to half an hour to get familiar with the setup before the actual trials began. There were two trials of ten minutes which were presented in a randomised order to the participants. In one trial, which we will denote as T1, users were required to perform a kinesthetic demonstration at a speed that they were comfortable with. After the demonstration, users had the possibility to correct the demonstration with the possibility to scale the attractor distance. To ensure that the main contribution to the velocity resulted from the scaling factor, the attractor ∆x itself was bounded to 4 cm. In the other trial, which will be denoted as T2, users were required to provide a fast kinesthetic demonstration. The attractor for this trial was left unbounded and any corrections that needed to be given for the velocity had to be performed by directly altering the attractor in the three Cartesian directions. A trial was considered successful if the final trajectory execution time was 4 s or less.

The goal of this study was two-fold; one for verifying the feasibility of allowing non-expert users to teach the robot in performing non-zero-velocity grasping and second, for determining which correction approach users may prefer.

TABLE II: Performance in Interactive Adaptation

|                  | Rigid (250 g) | Rigid (900 g) | Flexible (100 g) | Deformable and small (250 g) |
|------------------|---------------|---------------|------------------|-------------------------------|
| Total Training   | 108.89        | 31.33         | 0                | 124.26                        |
| Time [s]         |               |               |                  |                               |
| Rounds           | 7             | 2             | 0                | 10                            |
| Success [%]      | 90            | 90            | 70               | 100                           |

The study demonstrated the effectiveness of providing corrections before reaching that point. Which brings us to the second point, that due to the over-correction of the attractor, the velocity at the point which required large counter-corrections was very high. For someone with little experience with the setup, this can be a challenging situation to correct. This evidences interesting directions for future researches.

Nevertheless, overall good teaching performance could be observed in both trials. For T1, users were able to teach the task within, on average, 5.4 min with 19 correction rounds. The average time at which the robot could successfully grasp the object that they were able to teach was 3.4 s with the best time being 2.2 s. For reference, the time needed to demonstrate the behaviour at a fast pace in T2 was at best 3.9 s, but generally participants needed more than 5 s to carry out the demonstrations. It thus becomes clear that overall non-experts are not able to or are not comfortable with providing fast demonstrations. Provided a faster demonstration, the time needed for corrections however did tend to be lower.

Participants were also asked to fill in a NASA TLX questionnaire to assess the workload of the task for the two versions of the method. The results of the questionnaires were fairly similar for the two trials. Of the more noteworthy, both trials displayed high mental demand where for T1 the mental demand tended to be higher than T2. This can mainly be attributed to the greater number of inputs and the lack of intuitiveness of the input device. At the same time the reported frustration remained in the lower part of the scale, although T1 saw somewhat lower levels of frustration since in T2 the effects of over-correcting were more prominent.

Participants were also explicitly asked which correcting approach they preferred (T1 or T2). Between the participants, there was no clear preference towards one method or the other. Some preferred to correct the complete translational dynamics with one input, claiming that it made it easier to provide a nice shape to the trajectory or that it was more intuitive for altering the velocity since it compared more to how joystick inputs were translated to movements of the controlled character. Meanwhile, others found it easier to focus on correcting one aspect at a time, thus preferring to first correct the trajectory before increasing the velocity with the scaling factor.

To conclude, the study demonstrated the effectiveness
of the framework. It could be seen that when only using the kinesthetic demonstration, people generally could not attain the desired execution time even with a fast demonstration. However, with the help of corrections to the motion dynamics, an execution speed outside of their demonstration capabilities became achievable. The preferred means for providing these corrections varied between participants, which is why the final framework will enable the velocity corrections to be provided both in a coupled (with only $\Delta x$) and decoupled manner (with $\gamma$ and bounded $\Delta x$).

V. CONCLUSIONS AND FUTURE WORK

We demonstrate that the motion dynamics of a user’s demonstration can be successfully altered in a non-uniform manner using user corrections. This allows users to overcome the limitations they had during the demonstration and teach the actual desired behaviour. It further allows users to compensate for delays within the system which are not directly known to them but are observable in the system’s performance. It was additionally shown that non-experts are able to successfully teach a never-zero-velocity motion for grasping objects. Irrespective of their prior experience or lack with robots, they were able to successfully train this complex task, teaching and correcting the motion dynamics of many degrees of freedom.

Based on the results of the study, in future investigations, the manner in which users can alter the dynamics will remain free for the users to choose according to what they feel most comfortable with. To further improve usability and be able to remedy the effects of over-correcting even when outside the region of certainty, alternative solutions to providing corrections will be investigated, similarly to [4].

Certain aspects remain to be addressed for better generalisation and performance of the proposed framework. A next step would be to enable the correction of the desired orientation. While the current framework would allow for this extension, a better understanding of an intuitive input interface is needed. Moreover, the proposed framework could be parametrized with object and goal locations to allow generalisation of the policy to previously unseen workspace configurations, compensating the changes with the minimization of the policy uncertainty. Further work will focus on expanding the proposed algorithm to accommodate such a generalisation, potentially allowing the framework to be applied in scenarios involving dynamically changing environments.

In conclusion, in our opinion, with this study we understood that when learning familiar tasks like grasping, there is no better teacher than humans themselves that are learning from each other since it is the origin of our cooperation-based society.

REFERENCES

[1] Y. Wang, N. Dehio, A. Tanguy, and A. Kheddar, “Impact-aware task-space quadratic-programming control,” arXiv preprint arXiv:2006.01987, 2020.
[2] A. Billard and D. Kragic, “Trends and challenges in robot manipulation,” Science, vol. 364, no. 6446, 2019.
[3] H. Ravichandar, A. S. Polydoros, S. Chernova, and A. Billard, “Recent advances in robot learning from demonstration,” Annual Review of Control, Robotics, and Autonomous Systems, vol. 3, pp. 297–330, 2020.
[4] G. Franzese, A. Mészáros, L. Peternel, and J. Kober, “ILoSA: Interactive learning of stiffness and attractors,” in IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2021.
[5] B. Nemec, A. Ude et al., “Speed adaptation for self-improvement of skills learned from user demonstrations,” Robotics, vol. 34, no. 12, pp. 2806–2822, 2016.
[6] N. Uchityama, S. Sano, and K. Ryuman, “Control of a robotic manipulator for catching a falling raw egg to achieve human-robot soft physical interaction,” in 21st IEEE Int. Symp. on Robot and Human Interactive Communication (RO-MAN), 2012, pp. 777–784.
[7] S. S. M. Salehian, M. Khoramshahi, and A. Billard, “A dynamical system approach for softly catching a flying object: Theory and experiment,” IEEE Trans. on Robotics, vol. 32, no. 2, pp. 462–471, 2016.
[8] I. Havoutis, C. Semini, J. Buchli, and D. G. Caldwell, “Quadruped trotting with active compliance,” in IEEE Int. Conf. on Mechatronics (ICM), 2013, pp. 610–616.
[9] M. Bogdanovic, M. Khadiv, and L. Righetti, “Learning variable impedance control for contact sensitive tasks,” IEEE Robotics and Automation Letters, vol. 5, no. 4, pp. 6129–6136, 2020.
[10] S. Haddadin, A. Albu-Schäffer, and G. Hirzinger, “Requirements for safe robots: Measurements, analysis and new insights,” Int. Journal of Robotics Research, vol. 28, no. 11-12, pp. 1507–1527, 2009.
[11] D. Koert, J. Pajarinen, A. Schotschneider, S. Trick, C. Rothkopf, and J. Peters, “Learning intention aware online adaptation of movement primitives,” IEEE Robotics and Automation Letters, vol. 4, no. 4, pp. 3719–3726, 2019.
[12] A. Paraschos, C. Daniel, J. Peters, G. Neumann et al., “Probabilistic movement primitives,” Advances in Neural Information Processing Systems, 2013.
[13] B. Nemec, N. Likar, A. Gams, and A. Ude, “Human-robot cooperation with compliance adaptation along the motion trajectory,” Autonomous Robots, vol. 42, no. 5, pp. 1023–1035, 2018.
[14] R. Perez-Dattari, C. Celemin, G. Franzese, J. Ruiz-del Solar, and J. Kober, “Interactive learning of temporal features for control: Shaping policies and state representations from human feedback,” IEEE Robotics & Automation Magazine, vol. 27, no. 2, pp. 46–54, 2020.
[15] C. E. Rasmussen and C. K. I. Williams, Gaussian Processes for Machine Learning, The MIT Press, 2006.
[16] S. Kim, A. Shukla, and A. Billard, “Capturing objects in flight,” IEEE Trans. on Robotics, vol. 30, no. 5, pp. 1049–1065, 2014.
[17] S. M. Khansari-Zadeh and A. Billard, “Learning stable nonlinear dynamical systems with gaussian mixture models,” IEEE Trans. on Robotics, vol. 27, no. 5, pp. 943–957, 2011.
[18] K. Kronander, M. Khansari, and A. Billard, “Incremental motion learning with locally modulated dynamical systems,” Robotics and Autonomous Systems, vol. 70, pp. 52–62, 2015.
[19] M. Kelly, C. Sidrane, K. Driggs-Campbell, and M. J. Kochenderfer, “HG-DAgger: Interactive imitation learning with human experts,” in IEEE Int. Conf. Robot. Autom., 2019.