Learning Variable Impedance Control for Contact Sensitive Tasks

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Abstract: Reinforcement learning algorithms have shown great success in solving different problems ranging from playing video games to robotics. However, they struggle to solve delicate robotic problems, especially those involving contact interactions. Though in principle a policy outputting joint torques should be able to learn these tasks, in practice we see that they have difficulty to robustly solve the problem without any structure in the action space. In this paper, we investigate how the choice of action space can give robust performance in presence of contact uncertainties. We propose to learn a policy that outputs impedance and desired position in joint space as a function of system states without imposing any other structure to the problem. We compare the performance of this approach to torque and position control policies under different contact uncertainties. Extensive simulation results on two different systems, a hopper (floating-base) with intermittent contacts and a manipulator (fixed-base) wiping a table, show that our proposed approach outperforms policies outputting torque or position in terms of both learning rate and robustness to environment uncertainty.

Keywords: Reinforcement learning; Variable impedance control; Contact-rich tasks

1 Introduction

Many interesting robotic applications necessitate complex physical interactions with the environment. During locomotion, intermittent contacts and force modulation enable the robot to keep balance and move forward. Multi-contact interactions are also central to the efficient manipulation of objects. Establishing and breaking contact is especially hard because it causes a switch in the dynamics of the system which can rapidly lead to failures if not controlled properly. Unforeseen changes in the contacts location and properties (friction, stiffness, etc) can also dramatically degrade the robot behavior and remain a fundamental challenge in robotic manipulation and locomotion.

Deep reinforcement learning has shown a lot of promise in recent years for robotic applications. However, in an effort to learn end-to-end policies the focus has often been on the complexity in the observation part of the task, specifically vision, and not necessarily on the physical interaction part of the problem. One important aspect, that we investigate in the paper, relates to the choice of a policy parametrization that affords efficient learning of policies robust to contact uncertainties.

It was shown that position control with fixed pre-tuned gains can have better learning performance than pure torque outputs [1]. However, constant gains policies, i.e. policies that fix the mechanical impedance of the system, are likely to have robustness issues in face of uncertain contact interactions. Previous work has demonstrated the importance of some form of force control when learning interaction tasks, either explicitly [2] or by learning time-varying control gains [3, 4, 5, 6], state-varying feedforward and feedback gains [7], or unified motion and gains varying strategy [8, 9, 10]. Recent results [10] suggest that learning impedance schedules can significantly speed up learning of manipulation tasks. In particular, as in several other approaches [2, 6], an operational space representation was used, which has the advantage of abstracting the robot kinematics with the important
drawback of fixing the redundancy resolution scheme which can seriously limit the range of possible behaviors. Indeed, nullspace resolution is critical to enable the concurrent execution of several tasks necessary to achieve complex behaviors, e.g. avoiding an obstacle while reaching for an object or taking a step while maintaining balance [11, 12]. Moreover, there is evidence that the best choice for a task-space may vary across and within tasks [13].

As suggested by these approaches, representing control policy outputs as desired impedance and motion trajectories might be beneficial for interaction tasks. However, it is not clear if this choice has any effect on the ability to find policies that are more robust to uncertainties in the environment, especially contact locations, friction and rigidity. In this paper, we postulate that parametrizing the outputs of policies learned through deep reinforcement learning as variable impedance and desired positions can not only improve learning speed but, more importantly, increase the robustness of the policies. It has been shown [14] that an appropriate choice of mechanical impedance affords robust physical interactions without the need for an explicit measurement of interaction forces, therefore enabling intrinsically robust interactions. Moreover, the structure imposed on the learned policy affords an interesting interpretation: the desired position can be associated to the feedforward path of the policy, i.e. what needs to be done to achieve the task, while the impedance represents the feedback path, i.e. how the system reacts to unforeseen physical interactions. Such explicit distinction between causally different control paths is not possible in pure position or torque-based control. We expect that the learning algorithm will be able to leverage this distinction.

The main contribution of this paper is to demonstrate, through extensive numerical simulations, that control policies that output both desired positions and joint impedance can perform well both in-contact and during free motion, while being robust to uncertainties in contact switching and environment characteristics, which is inevitable in real-life applications. In particular, we perform an extensive set of simulations on two very different systems: a hopper (floating-base) with intermittent contacts and hard impact and a manipulator (fixed-base) wiping a table and compare our approach to torque-based and position-based policy outputs. We show that our approach i) systematically improves learning speed and ii) significantly increases policy robustness in face of uncertain contact locations, and unknown friction and stiffness.

2 Method

In this work, we compare several control policy parametrizations for manipulation and locomotion tasks. In this section, we first describe the reinforcement learning algorithm used, then provide details on each controller parametrization.

Reinforcement learning algorithm. For training the control policies we use Deep Deterministic Policy Gradient (DDPG, [15]). We chose an off-policy algorithm to reduce the issue of local minima, which is especially present when learning to control in joint space and when dealing with complex, multi-part reward functions. However, we do not exploit anything specific to DDPG in our approach and the expectation is that the controller design we propose here should work with other learning algorithms as well.

Each policy we describe bellow takes as input a state of the system, $\xi$, which contains the joint positions ($q$), joint velocities ($\dot{q}$), as well as potentially some additional observations on the system (for example measured endeffector force). Policy outputs vary between controllers and we will describe each one individually.
**Torque control (TC).** The first policy representation we investigate, which is often used in deep reinforcement learning, is one which directly outputs joint torques:

\[
\tau_i = \pi_i(\xi)
\]

This way, no structure is imposed by the controller and we have a direct mapping between measured states and control actions. However, this lack of structure brings forward several potential issues. First, exploring in the space of joint torques is difficult and often specific approaches, like using correlated noise to explore, need to be applied to enable learning. Second, small variations in the environment such as contact location, can lead to important changes in the required torques, causing difficulty to learn policies. Additionally, without any imposed control structure, it might be more difficult to ensure stability (e.g. through feedback gains) and robustness of learned policies.

**Position Control (PC).** The next approach we consider is controlling the desired joint positions with fixed gains:

\[
\tau_i = K_{pi} \cdot (\dot{q}_i^{des}(\xi) - q_i) - K_{di} \cdot \dot{q}_i
\]

This adds some structure to the problem and in a lot of cases solutions will be easier to find in this space [1]. It is, as we will also see in our experiments later, the best choice for tasks involving only free space motions. However, it can be problematic when uncertain interactions with the environment are involved. While it is possible to learn a fixed gains position control policy that will exert a desired force on the environment, through some form of implicit admittance control, this will necessarily be sensitive to unforeseen variations in the environment. Indeed, a small difference in contact location can result in excessive forces which is not acceptable in any real world applications.

**Variable Gain Control (VGC).** The approach we are proposing in this paper extends the previous controller to make it possible for the policy to not just provide desired position, but also vary the gains for each joint during execution. With this we aim to preserve the ease of learning, performance in free space motions and the imposed structure on the policy, while being able to control interaction forces more directly and most importantly being more robust to variations in the environment.

The policy output in this case consists of two parts: one controlling the desired joint positions \((P)\) and one controlling the gains \((Q)\). To define the range of potential gain values for each joint we assume we have access to some baseline gain values, \(K_{pi}^{base}\), for position control for each joint and use these values as midpoints. These values do not need to be fine tuned and are used just to give the order of magnitude for the gains of each joint, as they can differ significantly across joints. We then define the range as \(\left[\frac{1}{\sqrt{C}} \cdot K_{pi}^{base}, C \cdot K_{pi}^{base}\right]\) with the constant \(C\), shared between joints, defining the size of the range. We map the policy outputs controlling the gains, \(P_i(\xi)\), from the range \([-1, 1]\) to this range, with \(K_{pi} = C P_i(\xi) \cdot K_{pi}^{base}\). We also vary the velocity gains as the position gains change.

Starting from a baseline \(K_{di}^{base}\) value, we scale them following an ideal critical damping relationship using the square root of the position gain, with \(K_{di} = \sqrt{C P_i(\xi)} \cdot K_{di}^{base}\).

Putting everything together, the full control policy we apply is:

\[
\tau_i = C P_i(\xi) \cdot K_{pi}^{base} \cdot (\dot{q}_i^{des}(\xi) - q_i) - \sqrt{C P_i(\xi)} \cdot K_{di}^{base} \cdot \dot{q}_i
\]

We note here, that in contrast to the previous two controllers, we have introduced an extra degree of freedom (the gain modulation) for each joint. In theory, this added degree of freedom does not increase the capability of the system as everything is eventually transformed into a joint torque, it nevertheless allows an explicit separation between the task behavior (the desired position) and the response to unforeseen events (the feedback gain).

**Single Variable Gain Control (SVGC).** As a variant of the variable gain position control we also consider a version where a single output value of the policy is used to simultaneously modulate the gains for all the joints. The idea behind using this type of control is to examine if in some tasks the system does not need full freedom to vary the stiffness of each joint independently, but that there exists a single dimension along which the gain can be varied for all of them. If that is the case we would expect the reduction in the dimension of the policy output to speed up learning as well as potentially to gain more robustness from the additionally imposed structure.
Figure 2: Two setups used for evaluations. a) Fixed-base: a manipulator interacting with the environment. b) Floating-base: a hopper jumping on a surface.

Here the policy outputs a single value $P(\xi)$ and uses it across all the different joints. The full control policy in this case becomes:

$$
\tau_i(s) = C P(\xi) \cdot K^{\text{base}}_{pi} \cdot (Q_i(\xi) - q_i) - \sqrt{C P(\xi) \cdot K^{\text{base}}_{di} \cdot \dot{q}_i}
$$

(4)

3 Evaluation

To investigate how the different parametrizations affect learning contact tasks, and in particular the advantages of impedance learning, we study two physically different robots in simulation: a manipulator (fixed-base) performing a contact task on a table and a hopper (floating-base) jumping on the ground. The choice of two different setups is to show that our representation of action space is applicable to inherently different platforms and tasks involving interaction with uncertain environments. All the simulations in this section were performed with PyBullet [16] and used the DDPG implementation from OpenAI Baselines [17].

3.1 Fixed-base setup: a manipulator interacting with the environment

3.1.1 Description

Setup. We use a simulation of a 7 degree of freedom KUKA LWR manipulator (Figure 2(a)). In all the simulations, gravity is compensated with a feedforward term.

Task. The main task is doing a circular motion with the endeffector on the table in the environment in front of it, while applying a desired constant vertical force. This task is relevant for many applications such as cleaning a surface, performing a task using a tool on an object, etc. The task is designed such that the robot starts from a random initial position. It should be able to reach the table, establish a safe contact and exert a desired vertical force. We consider three types of uncertainties for the table: stiffness (i.e. how soft is the contact), friction, and height. These uncertainties are relevant for real-world applications as changes in contact properties and location can easily destabilize controllers and lead to failures. Moreover contact stiffness and friction cannot be known precisely before interaction in an unknown environment.

Reward function design. To learn a policy for achieving the desired task we define a reward function consisting of several parts (1-5). We use two terms to drive the circular motion along a desired trajectory: (1) the current distance from the endeffector to the closest point on the circle and (2) the difference between the current velocity vector and the desired tangential velocity on the closest point on the trajectory so as to achieve a motion with constant angular velocity. The three other terms are: (3) a reward based on the orientation of the endeffector, (4) a constant reward for any interaction between the endeffector and the table and a further reward based on the difference with desired contact force and (5) a penalty term for any interaction between the table and any part of the robot other than the endeffector. We consciously make a choice not to have a reward based on tracking a point periodically moving along the circle in order to ensure time-invariant policies.

In an effort to examine the ability of different controllers to learn free space motions, we also use a version of this task with the force part of the reward removed and without a table present in the environment. There the controller just needs to track the same circular trajectory, but now in free space. Compared with the previous task there is no need to optimize the interaction with the surface.
any more, however the lack of table to use as support also makes this not necessarily strictly an
easier task than the previous one.

3.1.2 Results

Evaluation method. We perform each policy training for a fixed, predefined number of episodes.
For each controller we repeat the training 6 times, with different circular trajectories to track. In
the plots we present the combined results, showing the mean and standard deviation for the learning
curves across these individual trainings.

Performance on both motion and interaction tasks. We first evaluate the performance of our
proposed approach on two qualitatively different tasks - one consisting of motion in free space, the
other of applying force and interacting with a surface. The learning curves for both are shown in
Figure 3. In the free space motion task (Figure 3(a)), the PC policy is, not unexpectedly, the fastest
to converge. While the learning progresses more slowly for the variable gain policies (VGC and
SVGC) they produce behavior that is as good at the end of the training. The TC policy on the other
hand converges to sub-optimal behavior.

In the task with force interaction (Figure 3(b)), the PC policy again initially learns the fastest (han-
dling the position part of the task), but other policies quickly catch up and overtake it (being able to
better handle the aspect of interaction with the environment). All the policies converge to adequate
behavior, but the SVGC policy separates itself from the others by being able to more consistently
and precisely perform the required action with reduced cost variance across experiments.

These two results suggest that variable gain control can preserve the best characteristics of both
position and torque control and is able to perform well in both free space and interaction tasks with
reduced variability across experiments.

Robustness to variability in the environment. Here we examine the robustness of our approach
to variability present in the environment. We consider in three separate simulations uncertainties
on table height, friction, and stiffness. For each of the three variables we define a possible range of
values and uniformly sample a new environment in each episode during training. We vary the table
height in a 20cm range from 0.8m to 1.0m and Coulomb friction coefficients in a range from 0 (no
friction) to 1. We also vary the rigidity of the surface (which can easily influence the stability of a
controller) with stiffness values from 50 to 500.

For the case with uncertainty in table height measurement (Figure 4(a)) the policies with variable
gains (VGC and SVGC) learn faster to perform the task, but, more importantly they clearly outper-
form both TC and PC policies in terms of performance. This is an interesting result which shows
that representing the policy as a combination of motion and impedance gives the controller enough
freedom to deal with uncertainties in contact location. Such a policy can be interpreted as having
a feedback term to perform a certain free space motion or constrained force exertion, while the
feedforward term is able to compensate for the error imposed due to uncertainties. The other interesting
observation is that VGC has a slightly better final performance compared to SVGC. This may be due
to the fact that capability of the robot to apply a certain force depends on its configuration. The robot
needs to use state-dependant variable gains at each joint in order to robustly achieve the task.
In the second case, we consider uncertainty in the friction coefficient between the robot end-effector and the table surface. Since the task is to exert force on the table while moving on a circle, friction has a crucial effect for the part of the task in contact. Investigation on uncertainty of the friction coefficient in this task is relevant as friction coefficients can vary widely across surfaces and are hard to estimate. As we can see in Figure 4(b), in this case, VGC outperforms other policies, both in terms of learning rate and final performance.

In the third case, we investigate the effects of surface stiffness on the performance of each controller. The most obvious point here again is that VGC performs significantly better than the other three policies in terms of performance robustness and learning rate. PC struggles to do the task and we can note that even adding a single variable to control the gains through SVGC does not help to improve its performance.

**Qualitative analysis on contact transition.** Further comparison between different cases in Figure 4 reveals that the performance gap between the variable gain policies and the other two (TC and PC) is more obvious when there is uncertainty in the contact location. Since the dynamics of the system changes before and after contact, transition between the two modes (i.e. free motion vs. in-contact) has a critical impact on the task achievement. Hence, the policy that is able to tolerate uncertainty in the mode transition can outperform other ones drastically. To investigate qualitatively the behaviour of different policies in this case, we plotted the corresponding normal interaction forces (Figure 5) for a representative experiment. We can clearly see that the applied force from VGC is smooth without loosing the contact. On the other hand, TC looses contact frequently while it is expected to exert a constant force, while PC generates force with high frequency oscillations. The VGC policies lead to better contact forces which can be realistically applied to a real system compared to the other two policies.
3.2 Floating-base setup: a hopper jumping on a surface

3.2.1 Description

Setup. The second setup we use in our evaluations consists of a floating-base with an attached two degrees of freedom leg and a fixed surface beneath it. We restrict the base to only move along the Z-axis which eliminates the falling down effect while still capturing the base motion and intermittent contacts during continuous jumping.

Task. The task is to achieve stable hopping motions when starting from an initial position on the ground. We also penalize the generation of hard impacts with the ground, as it is not something that would be acceptable on the real system. We are interested in motions where the system smoothly lands and pushes off, without any discontinuities in its velocity.

Reward function design. To generate hopping motions we intentionally keep the reward function as simple as possible. The main part of the reward is based on the height of the robot base at every timestep, with an increase for values that cannot be reached without leaving the ground. This term, on its own, is enough to produce consistent hopping motions. However, regardless of the controller design, policies trained on such a reward produce exactly the excessive impacts on the ground we are looking to avoid. In an effort to disincentivize such behavior we add an additional term in the reward function penalizing robot base acceleration.

Even though in this case we are dealing with a comparably simple system, this reward design creates a challenging learning problem. It is relatively easy for policies to get stuck in a local minima where the system is just held upright with its leg fully extended and not reach any hopping motion in their exploration. The addition of the base acceleration penalty makes the problem even more difficult as initial hopping motions are bound to result in penalty for bad landings larger than the reward received for jumping.

3.2.2 Results

Evaluation method. We perform the evaluation and present the results for this setup in the same way as for the previous one with results averaged over 6 different training runs for each controller. In this case we only vary the ground stiffness as the two other parameter variations did not influence the task outcome greatly.

Baseline task. As a baseline, we first present results for all controllers on the base version of the task, without any perturbations in the environment. The corresponding learning curves are shown in Figure 6(a). The approach using position control with fixed gains learns slowly and does not manage to solve the task in the end. On the other hand, VGC (as well as SVGC) performs as good as TC and both have no trouble in achieving the desired behavior. It seems that in this case having a single state-varying feedback gain performs as good as having more policy freedom. However, limiting the policy to have a state-varying feedforward term with fixed feedback through PC makes it unable to perform the task.
Figure 7: Analysis of learned hopping behavior of a VGC policy trained on a variable stiffness environment. Gray dashed lines mark the moments of impact of the foot with the ground.

**Robustness to variability in the environment.** We use the same approach for testing robustness as in the previous setup, by randomly sampling a value of an environment parameter from a defined range for each training episode. Here we only vary surface stiffness and we do so in the same range as in the fixed-based setup, from 50 to 500.

The results are shown in Figure 6(b). Here again we can see that VGC outperforms TC policy, while PC and SVGC fail to learn how to complete the task. The interesting point to note is that adding one state-varying value to control the gains to the PC policy through SVGC does not help to perform the task. This supports the fact that we need to give enough freedom to each control input of the system through VGC to enable the controller reliably and smoothly switch between contact modes.

**Qualitative analysis.** We also do a more detailed examination of the type of behavior produced by our proposed approach in this setup. Specifically, we look at the process of landing and pushing off the ground for one of the VGC policies trained on a variable stiffness environment (Figure 7)(b).

Starting from the point where the robot is in the air, we can see that the gains for the knee drop almost to zero before contact with the ground is made. This allows for a smooth landing with a very compliant leg which can be observed from the smooth behavior of the base position at contact and in the lack of spikes due to impact in the contact force. After landing, we observe the knee gains increase, allowing for a controlled push off from the ground. After leaving the ground, both of the gains go down, rendering the leg more compliant. This behaviour is especially interesting because having impacts not only can cause damage to the real system, but it also might cause a bounce of the foot which degrades the performance for the next jump.

**4 Conclusion**

In this paper, we have investigated the effect of action space representation on the performance and learning rate of contact-rich tasks in the presence of uncertainties. We have shown through extensive simulations on a fixed-base manipulator wiping a table and a hopper making intermittent contact with the ground that independently varying position and impedance of each joint yields superior performance compared to policies outputting directly joint torques or desired positions with fixed gains. Our results showed that the proposed VGC policy performs as good as position control with fixed gains in contact-free motions, while it enjoys the compliant behaviour of a force control for the in-contact phase. More importantly, the use of variable impedance leads to policies that are more robust to environment variations allowing the robots to smoothly transition from free motion to contact mode without generating high impact forces. This is of particular importance in order to safely transfer learned behaviors to real robots in unknown environments.
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