Learning to Close the Gap: Combining Task Frame Formalism and Reinforcement Learning for Compliant Vegetable Cutting

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Keywords: Compliant Manipulation, Reinforcement Learning, Task Frame Formalism.

Abstract: Compliant manipulation is a crucial skill for robots when they are supposed to act as helping hands in everyday household tasks. Still, nowadays, those skills are hand-crafted by experts which frequently requires labor-intensive, manual parameter tuning. Moreover, some tasks are too complex to be specified fully using a task specification. Learning these skills, by contrast, requires a high number of costly and potentially unsafe interactions with the environment. We present a compliant manipulation approach using reinforcement learning guided by the Task Frame Formalism, a task specification method. This allows us to specify the easy to model knowledge about a task while the robot learns the unmodeled components by reinforcement learning. We evaluate the approach by performing a compliant manipulation task with a KUKA LWR 4+ manipulator. The robot was able to learn force control policies directly on the robot without using any simulation.

1 INTRODUCTION

The demand for service robots has grown significantly in recent years. Nowadays, mainly simple household chores are performed by robots, e.g., vacuum cleaning. Nevertheless, the demand for robots that can aid, e.g., elderly or handicapped persons, in many more tasks is high. This requires systems that are simple to adapt to new applications without the need for complex handcrafting of each individual behavior by experts. We aim at providing a solution that allows a user to specify a task in a high-level task description, augmented with learned parameterized policies that close the gap between simple task specifications and complex task dynamics.

Many robotic manipulation tasks require compliant manipulation, where the robot needs to respond to the contact forces while executing a task. Tasks like cutting vegetables (depicted in Figure 1), opening doors, or cleaning surfaces, involve deliberate contact of the robot with the environment. Classical planning and control approaches fail to perform satisfactorily, here, due to the lack of precise models of contact forces and a high computational complexity (Kalakrishnan et al., 2011). Simplistic models for control, e.g., linear approximations and stiffness controllers, have been proposed for such cases, but they still need manual tuning (Duan et al., 2018).

Figure 1: Tasks like vegetable cutting require compliant manipulation. A combination of a task description and learning of the free variables allows a robot to quickly adapt to new situations.

Task specification approaches allow to specify a task by defining constraints for a motion without explicitly planning a trajectory (Mason, 1981). This includes constraining the movement in some directions while allowing or enforcing the motion into other directions. Such approaches simplify the definition of contact-rich tasks, because not all parameters of the problem instance have to be known beforehand. Still, many of the parameters used in a task specification need to be tuned manually, which is a tedious task

Padalkar, A., Nieuwenhuisen, M., Schneider, S. and Schulz, D.
Learning to Close the Gap: Combining Task Frame Formalism and Reinforcement Learning for Compliant Vegetable Cutting.
DOI: 10.5220/0009590602210231
In *Proceedings of the 17th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2020)*, pages 221-231
ISBN: 978-989-758-442-8

and requires a number of human interventions. Moreover, sometimes the task is too complex to be fully-specified.

Reinforcement learning (RL), on the other hand, has the advantage that skills to solve a problem can be learned without a handcrafted set of motions. An agent learns skills by exploring the environment and adopting the parameters which govern its behavior. Learning all parameters of a policy can be computationally very expensive and might require a large number of interactions with the environment. If executed with a real robot those are costly and potentially dangerous. Sometimes it is possible to learn the skills in a simulated environment, but this requires to model the problem accurately in simulation which might be even more complex as solving the initial task. The application of reinforcement learning is, thus, limited by the above reason.

For humans, learning a new task is often a combination of explanation and demonstration, followed by an improvement of the skill by experience. We propose to combine task specification methods and reinforcement learning to create a solution for a compliant manipulation task. By employing task-specific information using a formal task specification framework helps to reduce the number of interactions with the environment required by a reinforcement learning algorithm. Moreover, hard safety limits set by the task specification framework make the learning process safe.

Our main contribution in this paper is a working system that learns how to cut vegetables based on a specification of the known parameters of the task without simulation. As free parameter the cutting force is learned for different vegetables. This combination allows the robot to learn the cutting parameters for a new vegetable with only a few environment interactions.

2 RELATED WORK

The manipulation of only partially known objects is a challenging problem. It has been tackled with a variety of hand-crafted and automatically derived strategies so far. Furthermore, many manipulation tasks require compliant manipulation, where the robot needs to respond to the contact forces while executing a task (Kalakrishnan et al., 2011; Leidner et al., 2015).

Task Specification Methods. A task specification framework allows a programmer to specify the task in terms of a high-level description. The low-level motion commands are automatically derived from this specification. This framework simplifies the integration of robots into daily tasks where programming explicit motions is not a viable option (Bruyninckx and De Schutter, 1996). It can be seen as an interface layer between the robot control architecture and a high-level task planning framework.

Leidner (2017) presents a representation in the form of action templates that describe robot actions using symbolic representations and a geometric process model. The symbolic representation of the task—specified in the planning domain definition language (PDDL)—allows planners to consider actions in the high-level, abstract task plan The geometric representation of the task specifies the sequence of low-level movement sequences needed to execute these actions.

The instantaneous task specification and control framework (iTaSC) synthesizes control inputs based on provided task space constraints (De Schutter et al., 2007; Decré et al., 2009, 2013). This approach is very powerful in terms of obtaining an optimal controller, but requires the modeling of a large number of constraints and geometric uncertainties. Smits et al. (2008) present an systematic approach for modeling the instantaneous constraints and geometric uncertainties.

Mason (1981) present the idea behind the Task Frame Formalism (TFF) for specifying compliant tasks. Different control modes—position, velocity, or force control—are assigned to the individual axes of the task frame (Nägele et al., 2018). Bruyninckx and De Schutter (1996) use TFF to open doors. This framework doesn't consider the specification of task quality or motion quality related parameters like velocity damping or instantaneous sensory inputs.

Reinforcement Learning. Reinforcement learning in general requires many interactions of an agent with the environment to learn a reasonable policy. For robotic applications this is often prohibitively expensive, especially when trying to learn the complete value function for all possible state-action pairs.

Policy-search methods have the advantage that they learn the policy for taking actions directly based on the observable state of the robot. This mitigates the burden to learn a value function (Deisenroth et al., 2013; Polydoros and Nalpantidis, 2017). This reduces the required interactions with the environment. Furthermore, policy-search methods are computationally less expensive. Given these advantages, we focus on policy-search methods to solve the problem of compliant manipulation.

The REINFORCE algorithm is based on the maximum-likelihood approach, which uses the policy

gradient theorem for the estimation of the gradient of a policy (Deisenroth et al., 2013; Sutton and Barto, 2018). Actions are drawn from a Gaussian distributions and then executed by the robot for exploration. It has been successfully applied to problems with discrete state and action space as well as robotic control problems (Peters and Schaal, 2006; Sutton and Barto, 2018). It is a very generic algorithm suited for a variety of problem formulations, but the exploration noise added at every time step can render learning a policy on a real robot infeasible.

The path integral policy improvement (PI^2) algorithm (Theodorou et al., 2010a) is a widely used policy-search algorithm for trajectory optimization. Theodorou et al. (2010b) use it for teaching a robot to jump over a gap, Chebotar et al. (2017) for opening a door and grasping an object. In many examples, trajectories were learned by demonstration with dynamic motion primitives (DMP) and then further optimized for a particular task using the path integral approach. Nevertheless, PI^2 has limited applications in reinforcement learning to the trajectory optimization problems. Therefore, it is hard adopt it for learning compliant control policies for contact situations.

Nemec et al. (2017) propose a control algorithm by combining reinforcement learning with intelligent control to learn a force policy to open a door. They take into account the constraints of the door motion and the closed kinematic chain resulting from a firm grasp of the robot hand on the door handle. While opening the door in such configuration, high internal forces are generated in the directions where the motion is not possible. This knowledge is employed to learn a compliant force-control policy.

Policy learning by weighting exploration with the returns (PoWER) from Kober and Peters (2014) is an expectation-maximization-based learning algorithm. By adding the exploration noise for batches of exploration trials, it is well-suited for learning a force control policy on a real-robot system.

Our approach combines the features of model-based manipulation solutions and reinforcement learning. We formalize constraints in terms of already existing task specification methods, which can be generalized to a number of compliant manipulation tasks.

Vegetable Cutting. Lioutikov et al. (2016) solve the task of vegetable cutting by learning dynamic motion primitives (DMPs). Their approach does not consider vegetable cutting as a compliant manipulation problem. Thus, the contact forces are not taken into account during execution. As a result, multiple cutting motions are required to cut the vegetable completely. By contrast, we aim at cutting the vegetable in one swipe.

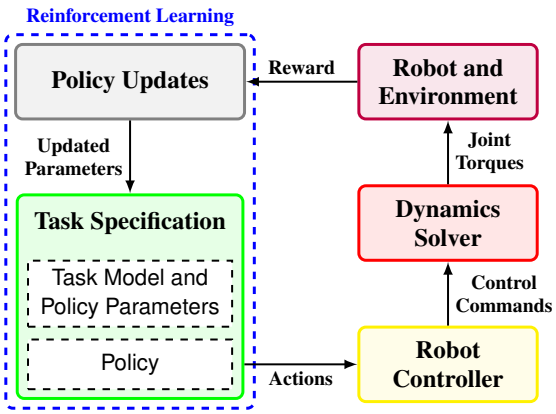


Figure 2: Outline of our architecture. The task specification contains defined twist and wrench setpoints, as well as the learned policy for the unmodeled parameters.

Lenz et al. (2015) approach the problem of cutting food by using a deep recurrent neural network with model predictive control. This neural network is trained offline with the collected cutting data to mimic the object dynamics. A controller generates control inputs, i.e., the force to be applied by the robot, by optimizing the control law for predicted states given a cost function. Furthermore, their task model is updated during the cutting process by observing the predicted and actual state of the system. The major drawback of this approach is the requirement of a large cutting dataset to learn the forward and backward models of the food to cut.

Mitsioni et al. (2019) extends this approach for a velocity and position controlled robot employing a force torque sensor.

3 APPROACH

We solve the compliant vegetable cutting task by providing an incomplete task specification in combination with reinforcement learning to learn the unmodeled components. As mentioned before, this has the advantage that the provided task specification will greatly reduce the number of dimensions of the reinforcement learning problem while keeping the necessary flexibility. Figure 2 outlines our proposed framework.

Our task specification contains the manually defined twist and wrench setpoints of the constrained endeffector dimensions in the defined task frame. Furthermore, it contains a learned policy for the unmodeled parameters. The policy is updated according

to the rewards after execution of the task. We employ an impedance controller that executes the motions synthesized by the task specification framework.

Task Specification. To facilitate the easy addition of new tasks to the system, their definition should be possible as abstract task description with task-oriented concepts. For the robot controller, nevertheless, this formulation has to be concrete enough to devise the robot motion commands (Bruyninckx and De Schutter, 1996). To achieve this goal, we employ the TFF framework (Mason, 1981), because it is well-suited to model contact situations during compliant manipulation. Sensor feedback is implicitly integrated when satisfying the modeled constraints, the motion specification can be updated online, and an appropriate task frame can be specified.

The TFF is based on the following assumptions: I) the robot and the manipulated object are rigid bodies, II) the constraint model of the manipulation task is simple, i.e., no non-linearities, like deformations and contact frictions, are modeled, III) the required force controller is simple and easy to implement on the robot, and IV) only kinetostatic concepts are used to implement the control, i.e., twists (linear and angular velocities), wrenches (forces and torques), and the reciprocity relationship between both.

TFF allows a programmer to specify a task by means of twist and wrench constraints in the task frame, extended by a stopping condition. For the proposed vegetable cutting task the above assumptions are partially satisfied as vegetables are not rigid bodies and cutting inherently implies the deformation of the body. We relax this assumption by defining constraints by a learned policy.

The basis of the TFF lies in the kinetostatic reciprocity of the manipulated object. The manipulated rigid object must execute an instantaneous rigid body motion $\mathrm{t} = [\omega^T \, v^T]^T$ that is reciprocal to all ideal, i.e., friction-less, reaction forces $\mathrm{w} = [f^T \, m^T]^T$ that the actual contact situation can possibly generate:

$$\omega^T m + v^T f = 0, \tag{1}$$

with angular velocity ω, linear velocity v, force f, and moment m. The moment is the sum of the applied external moment and the moment generated by the applied force. Equation (1) is the physical property that no power is generated against the reaction forces by the twist t. The twist and wrench spaces are always reciprocal in these type of contact situations. Adhering to this condition, a task can be fully specified in a suitable orthogonal reference frame by modeling all contact twist and force constraints. Such an orthogonal reference frame—the task frame—decouples twists and wrenches.

```
move compliantly {
  with task frame directions
  xt:  velocity 0
  yt:  velocity v(t)
  zt:  force f(environment, robot,
               task)
  axt: velocity 0
  ayt: velocity 0
  azt: velocity 0
} until distance y > d
```

Figure 3: Task specification for cutting vegetables.

A three-dimensional task frame has six programmable task frame directions: one linear velocity or force and one angular velocity or torque per axis. By the selection of a suitable task frame, a task can be fully specified by the definition of task constraints for all directions. These are satisfied by the application of twists and wrenches in the correct task frame directions and compliance in the other directions. Bruyninckx and De Schutter (1996) provide a detailed analysis for the selection of suitable task frames for a variety of tasks. The selection of a task frame starts with modeling natural constraints of the body, i.e., identifying the force controlled directions and the velocity or position controlled directions (Mason, 1981). This condition is called geometric compatibility of the task frame. The actions required for the completion of the task are then specified on top of these natural constraints in the same task frame. A chosen task frame should always remain compatible over time, i.e., the force controlled, and velocity or position controlled directions should not vary over time.

For vegetable cutting the task is represented in the chopping board frame, such that the Z-axis is perpendicular to the chopping board and the Y-axis is along the cutting direction. We refer to the movement in Y-direction as sawing motion and in downward Z-direction as cutting motion. These motions cannot be modeled or parameterized by constants, they are represented by parameterized policies. The advantage of the approach is that only the remaining free parameters need to be learned. This reduces the learning problem from six to one or, if the sawing motion should also be learned, two dimensions. Figure 3 shows our task description for vegetable cutting. $v(t)$ is the time-dependent sawing velocity and f is the cutting force in Z-direction, a function of the environment, the robot, and the task.

Reinforcement Learning. For choosing an appropriate reinforcement learning algorithm, the limitations of the robotic system and the applicability to

the task to solve have to be taken into account. The most important requirement is a fast convergence of the learned policy, as robot interactions with environment are costly and learning in simulation would be required, otherwise. Other challenges include I) a potentially high-dimensional continuous state and action space for compliant manipulation tasks, resulting in bad performance of value iteration-based approaches, II) complex transition dynamics of the robotic system, making the creation of a model hard, III) robot hardware, robot controllers, and contact-rich compliant tasks have damping properties by design, thus, all these components act as low pass filter, IV) close to real-time control requirements of robotic systems require a fast command update rate, requiring low computational cost algorithms. Furthermore, safe operation of the robot is crucial at all times during learning in order avoid damage to the robot and environment. In addition, the algorithm should be generic enough to optimize any arbitrary policy for a given cost function.

A model-free policy search algorithm for solving the learning problem matches these properties and requirements particularly well. We have selected the policy learning by weighting exploration with the returns (PoWER) algorithm, which is based on expectation maximization (Kober and Peters, 2014).

In the following, we will denote important definitions for the reinforcement learning algorithm. π_θ denotes the probabilistic policy for taking action a, given the current state s, parameterized by the policy parameters θ. It is differentiable with respect to θ. The probability of taking an action is governed by a Gaussian distribution, such that

$$a \sim \pi(\theta, s) \sim \mathcal{N}(\mu, \sigma), \tag{2}$$

where $\mu = f(\theta, s)$ is a function of the policy parameters θ and state s and is differentiable with respect to θ (Sutton and Barto, 2018). f can be any function approximator, e.g., splines, neural networks, or a linear combination of inputs. σ is the exploration noise added to each mean action μ.

The quality of the solution provided by executing policy π_θ is evaluated over a complete episode of T time steps. It is defined as performance measure

$$J(\theta) = \mathbb{E}[\sum_{t=0}^{T-1} r_{t+1}], \tag{3}$$

where r_{t+1} is the immediate reward received by performing action a_t in state s_t, specified by the reward function $R(a,s)$ (Sutton and Barto, 2018). The objective of the reinforcement learning process is to find the policy parameters that maximize this performance measure, also referred to as return.

This can be achieved by updating the policy parameters employing gradient ascent with the update rule

$$\theta_{i+1} = \theta_i + \frac{\partial}{\partial \theta} J(\theta_i). \tag{4}$$

$J(\theta)$ depends on reward r_{t+1}, which itself depends on action a_t taken in state s_t and resulting in state s_{t+1}. It means that $J(\theta)$ depends not only on action selections, but also on the state distribution (transition dynamics). In a given state s, it is straightforward to calculate the effect of the policy parameters on the reward r and, thus, on $J(\theta)$ from the knowledge of the effect of the policy parameters on the action a. Nevertheless, the effect of a policy on the state distribution is a function of the environment which is unknown.

The problem is to find the gradient of $J(\theta)$ with respect to θ, with the unknown transition dynamics of the environment. Employing the policy gradient theorem (Sutton and Barto, 2018) lets us rewrite the formulation to

$$\nabla_\theta J(\theta) = \sum_{t=0}^{T-1} \nabla_\theta log(\pi_\theta(a_i, s_i)) \sum_{t=0}^{T-1} r_{t+1}. \tag{5}$$

Since $J(\theta)$ is a function of θ as well as of the transition dynamics of the environment, the gradient is calculated by extracting information from trials conducted in the environment.

Expectation Maximization. Policy gradient methods show major drawbacks because of the state-independent unstructured exploration in the action space (Kober and Peters, 2009). The added Gaussian noise in the actions increases the variance of the parameter updates for longer episodes. Exploring the action space at each time step adds high-frequent noise to the robotic system which itself acts as a low-pass filter. As a result, the exploration signal vanishes. Furthermore, the unstructured exploration can damage the robotic system.

The expectation maximization-based method policy learning by weighting exploration with the returns (PoWER) from Kober and Peters (2014) uses state-dependent low-frequency noise for exploration It adds noise to the parameters at the beginning of a roll-out consisting of several trials instead of each action at every time step. Hence, the actions are constructed according to

$$a = f(\theta + \varepsilon, s_t), \tag{6}$$

where $\varepsilon \sim \mathcal{N}(0, \Sigma)$. To calculate the parameter update, the left hand side of Equation (5) can be set to zero in the case where π_θ belongs to the exponential

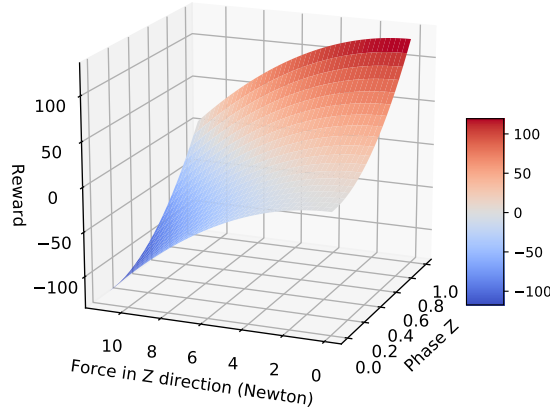


Figure 4: Example reward function surface for the vegetable cutting task.

family (Kober and Peters, 2014). As a result, we get the update rule

$$\theta_i' = \theta_i + \frac{\mathbb{E}[\sum_{t=0}^{T=1} \varepsilon_i r_{t+1}]}{\mathbb{E}[\sum_{t=0}^{T-1} r_{t+1}]}. \quad (7)$$

Reward Function. The employed reward function for learning the policy penalizes the applied force at each time step and gives a positive reward for progressing the cut in downward direction. It is given by

$$r = C_1 * \phi_z^2 - C_2 * f_z^2, \quad (8)$$

where ϕ_z is the downward progress normalized with the vegetable diameter and f_z is the applied force. C_1 and C_2 are positive constants that affect the behavior learned by the policy. Figure 4 shows the surface plot of the reward function with $C_1 = 100$ and $C_2 = 1$. At the end of the of each successful trial a positive terminal reward is awarded to the robot.

Reinforcement Learning for Cutting Vegetables with the TFF. As discussed earlier, the vegetable cutting task can be modeled with the TFF, but specifying the force required for cutting is not trivial. Hence, we propose to learn the downward cutting force employing reinforcement learning. The task frame for this task is depicted in Figure 5. We define the cutting progress by sawing phase ϕ_y—the motion parallel to the chopping board—and cutting phase ϕ_z—the downward motion—in Y and Z direction respectively as follows:

$$\phi_y = \frac{y_s - y}{y_d}, \quad (9)$$

$$\phi_z = \frac{z_s - z}{z_d}. \quad (10)$$

y and z are the partial position of the tool center point (TCP), y_s and z_s are the respective starting positions.

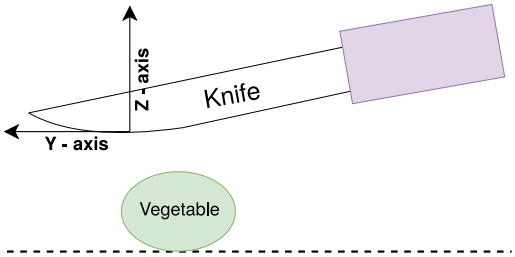


Figure 5: Task frame for the vegetable cutting task.

y_d is the desired sawing distance and z_d is the height, or circumference, of the vegetable. y_d can be specified as parameter in the task specification and the height of the vegetable z_d is measured online. The measurement is detailed in the evaluation section. ϕ_y and ϕ_z are dimensionless quantities and take values between 0 and 1.

Force Policy for Cutting Vegetables. We compare two force policy functions, a linear policy and a more expressive policy based on weighted Gaussian distributions. The linear policy is given by

$$f = -(A\dot{y} + B(0.5^2 - (0.5 - \phi_y)^2) + C(1 - \phi_z)), \quad (11)$$

where A, B, C are the policy parameters to be learned, collectively referred to as θ. If we interpret the physical meaning of this policy, $A\dot{y}$ can be seen as mechanical admittance, where A becomes the reciprocal of the admittance in Ns/m. The second term, $B(0.5^2 - (0.5 - \phi_y)^2)$, resembles that the applied cutting force should be higher in the middle of the sawing motion. With positive values of B, the second term becomes zero at the beginning (when $\phi_y = 0$) and end of the motion (when $\phi_y = 1$). It takes its maximum value at the middle of the sawing phase ($\phi_y = 0.5$) and it rises and falls exponentially. As ϕ_y is dimensionless, B is a force in Newton. The third term in the policy can be seen as an impedance provided by the vegetable to the motion of the knife during cutting. As ϕ_z is also dimensionless, C is a force in Newton, again. While designing the task, we tried to bring in the observed knowledge of general cutting tasks. Due to the limitations on observability, the policy may not completely capture the correct underlying dynamics of the task. Nevertheless, the task is modeled sufficiently well to learn a behavior that shows reasonable performance on the task.

To model more complex task dynamics, we employ a second more generic policy consisting of a weighted sum of equally-spaced Gaussian functions with centers lying in the interval $[0, 1]$. This Gaussian

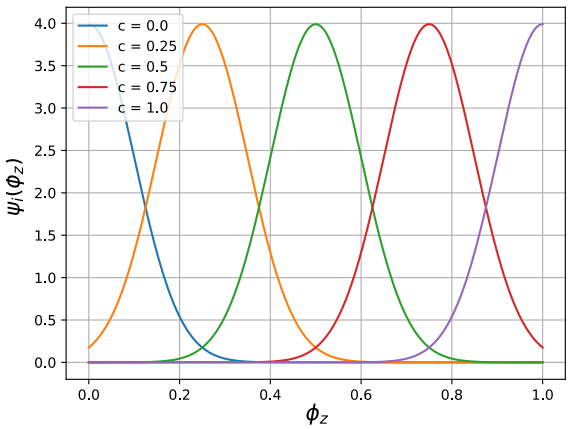


Figure 6: Five Gaussian functions with centers c placed equidistant on ϕ_z axis.

policy is given by

$$f = -(A\dot{y} + B(0.5^2 - (0.5 - \phi_y^2)) \quad (12)$$

$$+ \sum_{i=0}^{N-1} W\psi_i(\phi_z)), \quad (13)$$

$$\psi_i(\phi_z) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{(c_i - \phi_z)}{2\sigma^2}}, \quad (14)$$

where W is the weight vector, N is the number of Gaussian functions, c_i is the center of the i^{th} Gaussian, and σ is the width of each Gaussian function. This policy is more generic than the previously used policy as any arbitrary non-linear function can be approximated by a weighted sum of Gaussian functions. Here, we project the phase ϕ_z to a high dimensional non-linear space to capture the force distribution required at different phases of the cutting task. Figure 6 shows the Gaussian functions placed equidistantly on the phase axis.

The sawing motion can either be learned or it can be engineered. To keep the overall learning problem simple, we specify it as a continuous function of time in the task description. We have chosen a Gaussian function for the velocity profile as it has a smooth first order derivative, which represents acceleration in this particular case. This profile resembles human behavior, it can be fully parameterized by the distance to be traveled and the maximum velocity.

Robot Controller. For the realization of the above-mentioned high-level task specification framework, a motion controller is necessary to execute the task on the manipulator. If an accurate model of the environment is available then it is possible to calculate precise motion commands analytically to keep all contact forces within specified bounds while executing the task. For our application this would include an exact model of the soft vegetable, which is difficult to obtain. Thus, we employ a compliant controller that is able to respond to the contact forces to prevent damage to the robot and the environment.

Compliance in the motion can be achieved in two different ways: by impedance and by admittance control. Both approaches achieve the same goal of establishing a relationship between an external force and the resulting position error of the manipulator. We employ impedance control, where the robot hardware acts like a mechanical admittance (Ott et al., 2010). Here, the controller is designed to be a mechanical impedance. This resembles a loaded mass-spring system.

A torque-controlled manipulator with gravity compensation acts as a free-floating body constrained by its kinematic chain (Ott et al., 2010, 2015). To minimize a measured position error of the endeffector the controller increases the commanded forces on the endeffector. The applied force is directly proportional to the error. The impedance control scheme is defined by

$$\boldsymbol{F} = \boldsymbol{k}_c \boldsymbol{e} + \boldsymbol{D}(\dot{\boldsymbol{e}}), \quad (15)$$

$$\boldsymbol{e} = \boldsymbol{x}_{dsr} - \boldsymbol{x}_{msr}, \quad (16)$$

where $\boldsymbol{F}$ is the force generated at the endeffector by the manipulator, $\boldsymbol{k}_c$ is the stiffness of the manipulator, $\boldsymbol{D}(\dot{\boldsymbol{e}})$ is a damping term, $\boldsymbol{e}$ is the error in the desired position $\boldsymbol{x}_{dsr}$, and $\boldsymbol{x}_{msr}$ is the measured position of the endeffector. By using this control strategy along with the inverse dynamics equation of the manipulator, joint torque setpoints $\boldsymbol{\tau}_{cmd}$ can be calculated by

$$\boldsymbol{\tau}_{cmd} = \boldsymbol{J}^T(\boldsymbol{k}_c \boldsymbol{e} + \boldsymbol{D}(\dot{\boldsymbol{e}})) + f_{dynamics}(\ddot{\boldsymbol{q}}, \dot{\boldsymbol{q}}, \boldsymbol{q}), \quad (17)$$

where $f_{dynamics}(\ddot{\boldsymbol{q}}, \dot{\boldsymbol{q}}, \boldsymbol{q})$ is the joint torque vector required for the compensation of natural forces, dominated by gravity and friction. It is calculated by the dynamics solver of the manipulator.

4 EVALUATION

We evaluate our proposed solution with a KUKA LWR 4+ manipulator learning to cut cucumbers and bananas. For the cutting experiments, we mount an ordinary kitchen knife with a modified handle at the robot endeffector. The vegetable to cut is fixated using an adjustable clamp on top of a fixed chopping board such that it cannot move throughout the experiments. We place the vegetable such that its long axis is approximately perpendicular to the cutting motion, i.e., the x-axis of the specified task frame depicted in Figure 5. The knife is manually steered to a pose

above the first cut, we assume that this pose can be determined by an external perception system later. Figure 1 shows the setup.

At the beginning of the experiment the manipulator measures the height of the chopping board surface by approaching it with a downward motion until contact. The measured height is used throughout the entire experiment.

While learning the policy, the individual cutting trials start at one end of the vegetable. The manipulator moves along the x-axis after each cutting trial. The movement distance moves determines the size of the slices and can be configured by the user. Before performing a cut, the manipulator measures the diameter of the vegetable employing the same method as for measuring the height of the chopping board surface. With Equation (10) the normalized phase of the cut in the z-direction can be determined from the current position of the manipulator.

REINFORCE. After first promising simulation results, we tested the REINFORCE algorithm to learn the linear force policy for the cucumber cutting task given by Equation (11). The return is expected to increase over the training period, but the tests showed an opposite behavior, meaning that the algorithm was not able to learn the intended behavior. A probable explanation is that adding exploration noise at every time step is a high-frequency signal that is filtered by the low-pass dynamics of the system. First, the robot hardware acts as low-pass filter to this noise due to the inertia of the links, mechanical friction, and damping. Second, the Cartesian impedance controller resembles the behavior of a damped mass spring system. And third, the vegetable acts as a viscous medium and damps any movements through it. This impedes the exploration in the state-action space. Furthermore, the robot endeffector is vibrating as a result of the noise. The learning algorithm is unaware of these aspects and expects the force commands to be executed perfectly. As a result, the REINFORCE algorithm diverges during learning. This failure in learning the task shows that compliant manipulation tasks differ from trajectory optimization tasks. For the latter it is possible to execute motion commands with exploration noise at every time step and learn the policy effectively, according to the discussed literature.

PoWER with Linear Policy. Because of the above mentioned limitations on adding exploration noise at every time step, we employed the PoWER algorithm for subsequent experiments. PoWER adds exploration noise directly to the policy parameters at the beginning of each trial. The policy parameters to be learned are $\theta = (A, B, C)$ from Equation (11). The reward function (Equation (8)) is used with $C_1 = 100$ and $C_2 = 1$. A terminal reward of 1000 is given if the cucumber is completely cut through during the trial. The sawing motion is specified in the task description with a sawing distance of 10 cm and a maximum velocity of 5 cm/s.

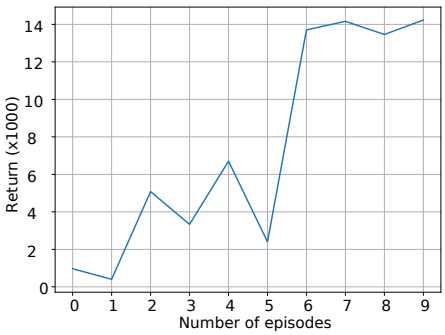


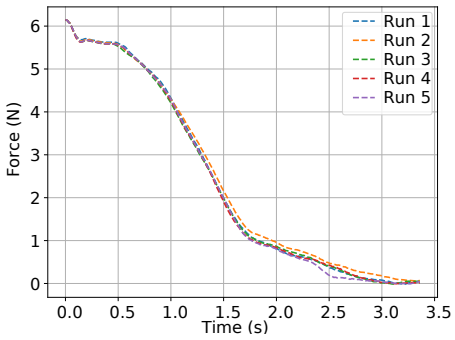
Figure 7: Learning progress of PoWER with linear policy. Depicted is the average return after each episode.

Each training episode consists of ten trials. The initial values of θ are $A = B = C = 0.5$. At the beginning of an episode, we sample new policy parameters $[\theta_1 \dots \theta_{10}]$ from the Gaussian distribution $\mathcal{N}(\theta, \Sigma)$, with $\Sigma = [1.5, 1.5, 1.5]$. The mean policy parameter vector θ is updated at the end of each episode.

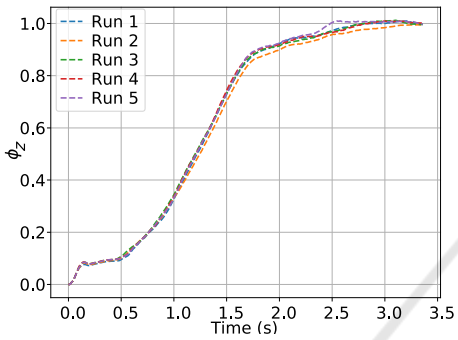
Figure 7 shows the average return of all trials in each episode. The algorithm converges after six episodes with a policy that can successfully cut through the cucumber in one swipe. Before the sixth episode, the return is largely affected by the depth of the previous cut. The finally-learned policy parameters are $A = -0.63$, $B = 1.56$, and $C = 6.15$. It can be observed that C contributes most to the generated force. According to our physical interpretation, this means that the policy has learned the impedance caused by the vegetable to the motion of the knife. The applied force and evolution of cutting phase are depicted in Figures 8a and 8b, respectively.

PoWER with Gaussian Policy. To evaluate our approach employing the more expressive Gaussian policy (Equation (14)), we let the robot learn to cut cucumbers and, in addition, bananas. Here, the policy parameters to be learned are $\theta = (A, B, W)$. We use five Gaussian functions with $\sigma = 0.15$.

For learning to cut cucumbers, we use the same reward function as before with $C_1 = 140$ and $C_2 = 1$. The terminal reward is 1500. We increased the value of C_1 to encourage a more aggressive application of force to cut through the vegetable. In this experiment, each episode contains 15 trials. The new parameter vectors $[\theta_1 \dots \theta_{15}]$ are sampled from a Gaussian dis-



(a) Force applied at TCP.



(b) Cutting phase ϕ_z.

Figure 8: Cutting motion of the knife in Z-direction with linear policy.

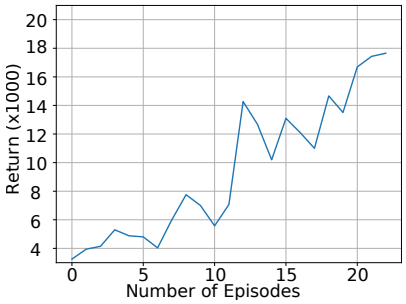
tribution with $\Sigma = (10, 1, [0.9, \ldots, 0.9]^T)$. The initial values of the parameters are $A = 15$, $B = 0.6$, and $W = [2, \ldots, 2]^T$.

Figure 9 shows the average return for learning the cucumber cutting task. The task could be learned within 20 episodes. To evaluate the learned policy, we ran multiple tests, in which the robot was able to cut through the cucumber completely every time. The learned parameter values are $A = 40.02$, $B = 2.08$, and $W = [1.84, 1.89, 1.79, 2.16, 3.56]^T$.

A better initialization and a high variance of the exploration noise helped in learning a suitable value of A, which represents the mechanical admittance. The robot learns a cutting motion with varying force depending on the cutting phase ϕ_z, represented by the different weights in W.

Figure 10a shows the applied cutting force for five test runs. The evolution of the cutting phase over time is depicted in Figure 10b for the same runs. It can be seen that the robot was able to reach the value $\phi_z = 1$ earlier than in the previous experiment. This means that the resulting cutting speed achieved with the Gaussian policy is higher than with the linear policy.

Values of ϕ_t that are slightly greater than one are explained by the slightly uneven surface of the chopping board caused by deformations from the clamp arrangement.



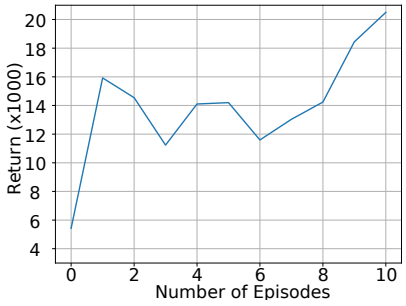
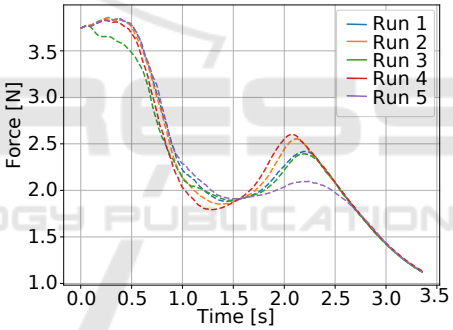
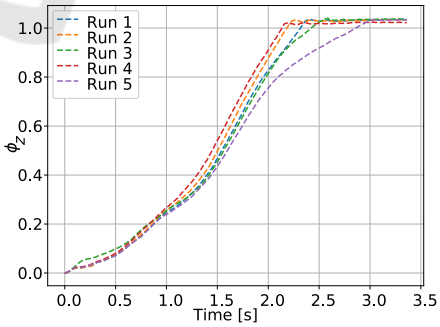


Figure 9: Learning progress of PoWER with Gaussian policy for cucumber (left) and banana (right) cutting.



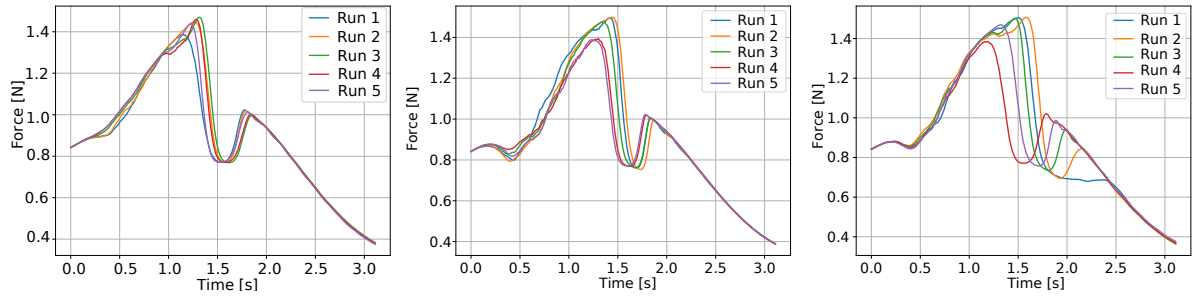
(a) Force applied at TCP.



(b) Cutting phase ϕ_z.

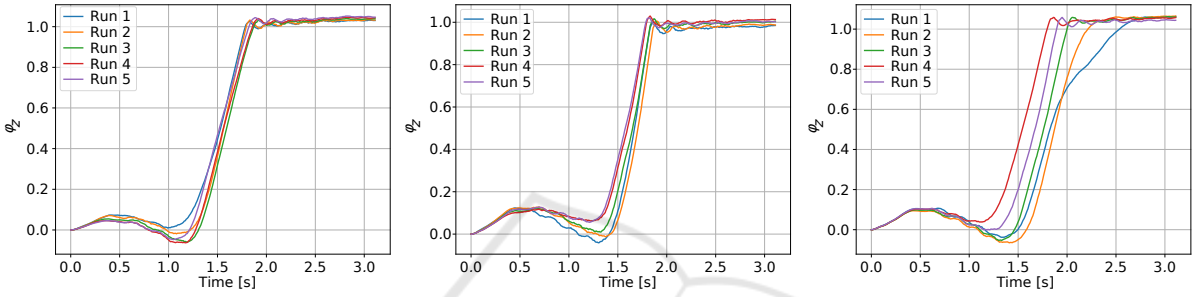
Figure 10: Cutting motion of the knife in Z-direction with Gaussian policy.

In addition to cutting cucumbers, we evaluated the approach by learning to cut bananas. Bananas are a



(a) 1 day old. (b) 2 days old. (c) 3 days old.

Figure 11: Force applied at TCP in Z-direction for cutting bananas with different ripeness.



(a) 1 day old. (b) 2 days old. (c) 3 days old.

Figure 12: Phase ϕ_z evolution of the cutting motion in Z-direction for cutting bananas with different ripeness.

different class of vegetables with a harder skin and a soft core. As the slices of the banana tend to stick together after cutting, we make sure that they are completely cut and removed by a cleaning motion after each trial. This is necessary to ensure similar starting conditions in each cutting attempt. Due to the resulting reduced variance the task could be learned in 9 trials, less that half of the trials required to learn to cut cucumbers. Figure 11 shows the force required for cutting bananas with different ripeness and Figure 12 shows the corresponding cutting progress. The learning progress is depicted in Figure 9.

5 CONCLUSIONS

We implemented and evaluated the ability of the TFF aided by reinforcement learning for the task of cutting vegetables. The introduction of reinforcement learning generalizes the TFF for tasks with hard to model parameters. On the other hand, employing the the Task Frame Formalism simplified the reinforcement learning problem to learn a one dimensional force policy. Experiments with a KUKA LWR 4+ manipulator demonstrated that the robot was able to learn a linear policy for cutting vegetables within six episodes and a Gaussian policy within twenty episodes. With careful modeling of the task, even complicated tasks with complex contact force dynamics can be learned directly with the robot without using any simulation. All learned policies were able to cut the vegetables completely in one swipe. In addition, the use of the the Fask Frame Formalism facilitated safe operation of the robot by a deterministic motion specification in the remaining five direction, including the sawing motion.

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