Transferring Knowledge for Reinforcement Learning in Contact-Rich Manipulation

Quanta0 Yang, Johannes A. Stork, and Todor Stoyanov

I. INTRODUCTION

While humans are adept in transferring a learned skill—that is the ability of solving a task—to a new similar task efficiently, most state-of-the-art reinforcement learning (RL) methods have to solve every new task from scratch. Consequently, millions of new interactions with different environments may be required to solve variant tasks, which is infeasible for a real robot system. Training from scratch is resource and time consuming, while sample collection in a new physical environment is costly and repetitive. Therefore, in order to apply RL directly on real physical robots, it is imperative to address the problem of sample-inefficiency when solving variant tasks.

State-of-the-art methods require policy training in simulation to prevent undesired behavior and later domain transfer, or guided policy search for single skills in a family of similar problems [1], [2], [3]. The successful deployment of simulation-to-reality methods requires that the simulation is close enough to the physical system. However, for real world robotic applications, transition dynamics in deployment are often substantially different from those encountered during training (in simulation).

In this work, we consider the problem of transferring knowledge within a family of similar tasks. Our fundamental assumption is that we are presented with a family of problems, formalized as Markov Decision Processes (MDPs) that all share the same state and action spaces [4]. Crucially however, we allow for members of the family to exhibit different transition dynamics. Informally, our assumption is that while transition probabilities are different, they may be correlated or overlapping for parts of the state space. We then propose a method—Multi-Prior Regularized RL (MPR-RL)—that leverages prior experience collected on a subset of the problems in the MDP family to efficiently learn a policy in a new environment.

II. APPROACH

Our approach to transferring knowledge for RL is based on exploiting prior knowledge from demonstrations for learning a policy in a new task. The process is composed of two distinct phases: a prior learning phase and a task learning phase. In the task learning phase, we guide the policy learning to initially follow skill priors learned in the prior learning phase. For this, we regularize the RL objective with a relative entropy term based on the learned skill priors.

We consider a family of tasks each formalized as a Markov decision process (MDP) defined by a tuple \((S,A,T,r, \rho, \gamma)\) of states, actions, transition probability, reward, initial state distribution, and discount factor. A family of MDPs \(\mathcal{M}\), share the same state and action space, while the dynamics and transition probabilities are different.

We assume access to a dataset \(D\) of demonstrated trajectories \(\tau_i = \{(s_0, a_0), \ldots, (s_{T_i}, a_{T_i})\}\) for each robotic task. We aim to leverage these trajectories to learn a skill prior \(p_i(a|s)\) for each specific MDP \(M_i\). Our objective is then to learn a policy \(\pi_\theta(z|s)\) with parameter \(\theta\) that maximizes the sum of rewards \(G(\theta)\) for a new MDP \(M_{new}\) by leveraging the prior experience contained in the dataset \(D\).

In skill prior RL (SPiRL) [5], the learned skill prior is leveraged to guide learning a high-level policy \(\pi_\theta(z|s)\) by introducing an entropy term. They propose to replace the entropy term of Soft Actor-Critic (SAC) [6] with the negated KL divergence between the policy and the prior. Similarly, our method uses the embedding space \(Z\).

Using only one skill prior limits the method to policy learning in the same task as where the skill prior was learned. For this reason, we extend this approach from one learned skill prior to several skill priors learned in different tasks.

To this end, we regularize the RL objective with a weighted sum of relative entropies:

\[
J(\theta) = \mathbb{E}_{\tau \sim \pi_\theta} \left[ \sum_{t=0}^{T} \gamma^t r(s_t, a_t, s_{t'}) + \alpha \Gamma_t \right],
\]

where

\[
\Gamma_t = -\sum_{i=1}^{m} \omega_i D_{KL}(\pi_\theta(\alpha_t|s_t), p_i(\alpha_t|s_t)).
\]

\(\omega_i\) is the adaptive weight and \(\sum_{i=1}^{m} \omega_i = 1\). \(p_i(\alpha_t|s_t)\) are skill priors from different tasks of the family. This means that the policy is initially incentivized to explore according to a mixture of different skill priors depending on the weight factors. We learn the adaptive weights \(\omega_i\) by training a discriminator for the most recent observed transition.

*This work was supported by the Wallenberg AI, Autonomous Systems and Software Program (WASP) funded by Knut and Alice Wallenberg Foundation.

Autonomous Mobile Manipulation (AMM) Lab, Örebro University, Sweden (e-mail: quantao.yang@oru.se; johannes.stork@oru.se; toodor.stoyanov@oru.se).
although it converges the reward plateau slower. MPR-RL weight is able to learn to insert the target peg in the new MDP faster, which is expected. MPR-RL policy with adaptive trained using three different seeds. We can see that SPiRL and square peg-in-hole tasks respectively. Each method is MPR-RL method and baselines over the real world hexagon Cartesian components. K is the variable stiffness matrix axis, and (3) the diagonal coefficients k Cartesian space, (2) rotational angle thus composed of: (1) end-effector translations ∈ SE(3) in Cartesian space and variable stiffness matrix K. Stiffness matrix K contains 6-dimensional end-effector stiffness coefficients. One extra null-space stiffness coefficient for the redundant robot is set as a constant value. Our 8-dimensional action space is 6×6 is incorporated into the agent action [7]. Therefore, we extend the policy action as the combination of end-effector pose ∈ 4 that determine the variable stiffness matrix K for the corresponding four Cartesian components.

The contact-rich peg-in-hole tasks, we use four different shapes as a family of MDPs: circular, hexagon, square and triangular as shown in Fig. 2(a). The different shapes induce different contact dynamics and thus modify the transition probabilities of the MDPs in the family. We test two cases: (1) inserting hexagon peg by using prior knowledge from circular, square and triangular ones; (2) inserting square peg by using prior knowledge from circular, hexagon and triangular ones. These two cases offer the possibility to interpolate between some of the other shapes.

To train skill prior RL on the real robot directly, the system stiffness term K ∈ R6×6 is incorporated into the agent action [7]. Therefore, we extend the policy action as the combination of end-effector pose ∈ SE(3) in Cartesian space and variable stiffness matrix K. Stiffness matrix K contains 6-dimensional end-effector stiffness coefficients. One extra null-space stiffness coefficient for the redundant robot is set as a constant value. Our 8-dimensional action space is thus composed of: (1) end-effector translations x ∈ R3 in Cartesian space, (2) rotational angle θz ∈ R around the z axis, and (3) the diagonal coefficients k ∈ R4 that determine the variable stiffness matrix K for the corresponding four Cartesian components.

Fig. 1(a) and Fig. 1(b) show the learning curves of our MPR-RL method and baselines over the real world hexagon and square peg-in-hole tasks respectively. Each method is trained using three different seeds. We can see that SPiRL with prior knowledge of the current MDP learns slightly faster, which is expected. MPR-RL policy with adaptive weight is able to learn to insert the target peg in the new MDP although it converges the reward plateau slower. MPR-RL

We evaluate the performance of MPR-RL using adaptive weights and compare with several baseline methods: (1) MPR-RL hard-max weight, where only the skill prior with the maximum task likelihood under the transition is used, (2) MPR-RL uniform weight, (3) SPiRL without prior knowledge from the target task, (4) Soft Actor-Critic (SAC), and (5) Behavioral Cloning with SAC (BC+SAC). When SPiRL has full access to the demonstration data from the target task, it is a baseline that is provided as a best-case oracle target.

In the contact-rich peg-in-hole tasks, we use four different shapes as a family of MDPs: circular, hexagon, square and triangular as shown in Fig. 2(a). The different shapes induce different contact dynamics and thus modify the transition probabilities of the MDPs in the family. We test two cases: (1) inserting hexagon peg by using prior knowledge from circular, square and triangular ones; (2) inserting square peg by using prior knowledge from circular, hexagon and triangular ones. These two cases offer the possibility to interpolate between some of the other shapes.

To train skill prior RL on the real robot directly, the system stiffness term K ∈ R6×6 is incorporated into the agent action [7]. Therefore, we extend the policy action as the combination of end-effector pose ∈ SE(3) in Cartesian space and variable stiffness matrix K. Stiffness matrix K contains 6-dimensional end-effector stiffness coefficients. One extra null-space stiffness coefficient for the redundant robot is set as a constant value. Our 8-dimensional action space is thus composed of: (1) end-effector translations x ∈ R3 in Cartesian space, (2) rotational angle θz ∈ R around the z axis, and (3) the diagonal coefficients k ∈ R4 that determine the variable stiffness matrix K for the corresponding four Cartesian components.

Fig. 1(a) and Fig. 1(b) show the learning curves of our MPR-RL method and baselines over the real world hexagon and square peg-in-hole tasks respectively. Each method is trained using three different seeds. We can see that SPiRL with prior knowledge of the current MDP learns slightly faster, which is expected. MPR-RL policy with adaptive weight is able to learn to insert the target peg in the new MDP although it converges the reward plateau slower. MPR-RL

We compare one example of action sequences generated when using different skill priors in a hexagon peg-in-hole task shown in Fig. 2(b). Each trajectory is an action segment of 10 waypoints and the red point shows the position of the target hole. It can be seen that our MPR-RL method combines the knowledge from three different MDPs circular, square and triangular and transfer the inserting skill to a new hexagon MDP. In this specific case, the action sequence from multi-prior is more similar to the circular one.

We have presented an approach that learns multiple priors for a family of similar MDPs and compose these priors to guide the RL training of a policy on a new MDP. Our approach learns prior knowledge over specific skills for similar tasks. By incorporating variable impedance into RL actions, we also show that our MPR-RL can be deployed directly on the real robot.

### III. RESULTS

We evaluate the performance of MPR-RL using adaptive weights and compare with several baseline methods: (1) MPR-RL hard-max weight, where only the skill prior with the maximum task likelihood under the transition is used, (2) MPR-RL uniform weight, (3) SPiRL without prior knowledge from the target task, (4) Soft Actor-Critic (SAC), and (5) Behavioral Cloning with SAC (BC+SAC). When SPiRL has full access to the demonstration data from the target task, it is a baseline that is provided as a best-case oracle target.

In the contact-rich peg-in-hole tasks, we use four different shapes as a family of MDPs: circular, hexagon, square and triangular as shown in Fig. 2(a). The different shapes induce different contact dynamics and thus modify the transition probabilities of the MDPs in the family. We test two cases: (1) inserting hexagon peg by using prior knowledge from circular, square and triangular ones; (2) inserting square peg by using prior knowledge from circular, hexagon and triangular ones. These two cases offer the possibility to interpolate between some of the other shapes.

To train skill prior RL on the real robot directly, the system stiffness term K ∈ R6×6 is incorporated into the agent action [7]. Therefore, we extend the policy action as the combination of end-effector pose ∈ SE(3) in Cartesian space and variable stiffness matrix K. Stiffness matrix K contains 6-dimensional end-effector stiffness coefficients. One extra null-space stiffness coefficient for the redundant robot is set as a constant value. Our 8-dimensional action space is thus composed of: (1) end-effector translations x ∈ R3 in Cartesian space, (2) rotational angle θz ∈ R around the z axis, and (3) the diagonal coefficients k ∈ R4 that determine the variable stiffness matrix K for the corresponding four Cartesian components.

Fig. 1(a) and Fig. 1(b) show the learning curves of our MPR-RL method and baselines over the real world hexagon and square peg-in-hole tasks respectively. Each method is trained using three different seeds. We can see that SPiRL with prior knowledge of the current MDP learns slightly faster, which is expected. MPR-RL policy with adaptive weight is able to learn to insert the target peg in the new MDP although it converges the reward plateau slower. MPR-RL

We compare one example of action sequences generated when using different skill priors in a hexagon peg-in-hole task shown in Fig. 2(b). Each trajectory is an action segment of 10 waypoints and the red point shows the position of the target hole. It can be seen that our MPR-RL method combines the knowledge from three different MDPs circular, square and triangular and transfer the inserting skill to a new hexagon MDP. In this specific case, the action sequence from multi-prior is more similar to the circular one.

We have presented an approach that learns multiple priors for a family of similar MDPs and compose these priors to guide the RL training of a policy on a new MDP. Our approach learns prior knowledge over specific skills for similar tasks. By incorporating variable impedance into RL actions, we also show that our MPR-RL can be deployed directly on the real robot.

### REFERENCES

[1] X. B. Peng, M. Andrychowicz, W. Zaremba, and P. Abbeel, “Sim-to-real transfer of robotic control with dynamics randomization,” in 2018 IEEE international conference on robotics and automation (ICRA). IEEE, 2018, pp. 3803–3810.

[2] M. Hazara and V. Kyrki, “Transferring generalizable motor primitives from simulation to real world,” IEEE Robotics and Automation Letters, vol. 4, no. 2, pp. 2172–2179, 2019.

[3] Y. Du, O. Watkins, T. Darrell, P. Abbeel, and D. Pathak, “Auto-tuned sim-to-real transfer,” in 2021 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2021, pp. 1290–1296.

[4] Q. Yang, J. A. Stork, and T. Stoyanov, “Mpr-rl: Multi-prior regularized reinforcement learning for knowledge transfer,” IEEE Robotics and Automation Letters, vol. 7, no. 3, pp. 7652–7659, 2022.

[5] K. Persch, Y. Lee, and J. J. Lim, “Accelerating reinforcement learning with learned skill priors,” in Conference on Robot Learning (CoRL), 2020.

[6] T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine, “Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor,” in International conference on machine learning. PMLR, 2018, pp. 1861–1870.

[7] Q. Yang, A. Durr, E. A. Topp, J. A. Stork, and T. Stoyanov, “Variable impedance skill learning for contact-rich manipulation,” IEEE Robotics and Automation Letters, 2022.