Adaptive Conditional Neural Movement Primitives via Representation Sharing Between Supervised and Reinforcement Learning

M. Tuluhan Akbulut 1, M. Yunus Seker 1, Ahmet E. Tekden 1, Yukie Nagai 2, Erhan Oztop 3 and Emre Ugur 1

Abstract—Learning by Demonstration provides a sample efficient way to equip robots with complex sensorimotor skills in supervised manner. Several movement primitive representations can be used for flexible motor representation and learning. A recent state-of-the-art approach is Conditional Neural Movement Primitives (CNMP) that can learn non-linear relations between environment parameters and complex multi-modal trajectories from a few expert demonstrations by forming powerful latent space representations. In this study, to improve the applicability of CNMP to changing tasks and/or environments, we couple it with a reinforcement learning agent that exploits the formed representations by the original CNMP network, and learns to generate synthetic demonstrations for further learning. This enables the CNMP network to generalize to new environments by adapting its internal representations. In the current implementation, the reinforcement learning agent is triggered when a failure in task execution is detected, and the CNMP is trained with the newly discovered demonstration (trajectory), which shares essential characteristics with the original demonstrations due to the representation sharing. As a result, the overall system increases its capacity and handles situations in scenarios where the initial CNMP network can not produce a useful trajectory. To show the validity of our proposed model, we compare our approach with original CNMP work and other movement primitives approaches. Furthermore, we present the experimental results from the implementation of the proposed model on real robotics setups, which indicate the applicability of our approach as an effective adaptive learning by demonstration system.

1. INTRODUCTION

In the last decade, robot learning has become a key technology for equipping robots with dexterous robot skills. From a learning point of view, acquiring robotic skills involve learning of multi-modal sensorimotor relations in connection with external parameters and goals. One fruitful robot learning framework is learning by demonstration (LfD), where expert task execution samples are provided for robot to learn from [1], [2]. If the demonstration can be obtained in the intrinsic coordinates of the robot, the expert demonstration can be played back on the robot [3] or state-to-action mapping can be captured by a neural network to synthesize a controller (e.g. [4]). Another common use of LfD is to initialize the policy search for a reinforcement learning (RL) agent for speeding up exploration [5], which also allows the simulation-to-real transfer with additional reinforcement learning on the real hardware. Although deep reinforcement learning can be used to synthesize non-trivial skills from scratch in simulation [6], [7], [8], for most robotic hardware, it is not feasible to implement direct deep reinforcement learning due to wear, time and energy cost as the number of samples for successful learning is too many [9]. Thus again, LfD based approaches are sought, where LfD provides expert knowledge about the task execution, effectively giving a prior to constrain policy search so that a solution can be found faster and safer. In contrast to simple playback of the shown trajectories, existing state-of-the-art LfD frameworks examine the given data and extract features from the demonstration in order to generalize the given task to a high number of situations/conditions. However, because LfD frameworks work only upon the given demonstration set, the quality and generalization capability of the learned system are highly dependent on the training data. While this approach can be suitable for non-stationary task domains, the robot may be required to quickly adapt to new environments or task requirements. In these cases, a new set of demonstrations can be collected, or if the whole system is designed as an RL system (as in [5]), the adaptation to new context can be undertaken by RL.

In this paper we propose a framework that keeps the supervised learning of LfD at the core, while utilizing RL for generating synthetic trajectories for LfD. This essentially keeps the robustness and efficiency of the supervised learning implementing LfD while allowing RL to find new trajectories efficiently. The efficiency is achieved by sharing the formed representations from the LfD process. With the representation sharing, the proposed system can discover skill variants which are not viable with the given range of demonstrations, but yet show the basic characteristics of the demonstrated skills.

We select Conditional Neural Movement Primitives[10] as our base LfD architecture. Bringing together the advantages of Gaussian Processes and deep neural networks, CNMP learns the relationships from the given demonstration set itself by sampling multiple numbers of observations and predicting conditional probability distributions over target time-steps. By encoding the sampled observations using a parameter sharing encoder, CNMP constructs a highly representative latent space, thus allows the system to generalize these learned complex and non-linear relations at the test time for given novel goal points of any time-steps. Successfully handling multiple types of state-of-the-art challenges on a single framework, CNMP takes one step forward as a powerful LfD method compared to the other methods.

1M. Tuluhan Akbulut, M. Yunus Seker, Ahmet E. Tekden ve Emre Ugur are with Department of Computer Engineering, Bogazici University, Istanbul, Turkey. 2Yukie Nagai is with International Research Center for Neurointelligence, University of Tokyo, Tokyo, Japan. 3Erhan Oztop is with Osaka University, Osaka, Japan.

https://github.com/mtuluhanakbulut/ACNMP
For goals that are inside of the training range (we call these points as interpolation points), CNMPs can easily learn high dimensional, complex trajectories, extract non-linear relations, and generate online trajectories at the test time. However, as the authors described in the paper, when given goals are starting to move outside of the training range (we call these points as extrapolation points), the performance and the quality of the generated trajectories decrease over time because of the nature of deep neural networks.

In this work, we extend the knowledge of Conditional Neural Movement Primitives with Reinforcement Learning and propose a method to overcome the limitations of the training set range. When a failure is detected by the system, our reinforcement learning agent steps in, and based on the learned experiences from the CNMP through its encoded representations, it finds a new trajectory that satisfies the failed task constraints. Our method allows our RL agent to explore and learn relationships outside of the training range while it still preserves the characteristics of the given demonstrations. After finding a novel, yet, similar characterized solution, the new trajectory is added to the training set of the CNMP and allows our system to learn new relationships and increase generalization capability.

Since our concept is built on the interpolation and extrapolation dilemma in neural networks, this approach can be seen as an attempt to increase generalization capabilities of deep neural networks to the outside of its data-set by reinforcement learning.

From the reinforcement learning perspective, we are using a probabilistic framework, which builds a representation of all possible solutions for the task and selects one of them in run-time for the specified constraints. When the knowledge is not enough and lead the agent to a failure, the agent starts exploration and finds a new trajectory.

II. RELATED WORK

A. Learning Movement Primitives from Demonstrations

LfD[1] is a paradigm where an end user teaches an agent action policies by providing expert demonstrations. Although LfD has been extensively used in robotic problems including object grasping and manipulation[11], [12], [13], [14], [15], researchers still face significant challenges such as automatic detection of relevant features, important aspects of the demonstrations, expense of data collection, automatic extraction of goals, learning complex relations between environmental variables and complex motion trajectories from preferably small amount of data, etc. Among others, learning methods that are based on dynamic systems [16] and statistical modeling [17] have been popular in the recent years. Dynamic Movement Primitives (DMPs) encode the demonstrated trajectory as a set of differential equations, implementing a spring-mass-damper system extended with a non-linear function in order to preserve learned shape of the movement with guarantee of reaching to the goal state. It offers advantages such as one shot learning of non-linear movements, real-time stability and robustness under perturbations, generalization of the movement for different goals, and linear combination of parameters. Encountered with novel situations, the model parameters that encode the non-linear movement of the DMP can be adjusted using Reinforcement Learning [18], [19]. Therefore, how well the system can learn complex tasks and how well it can generalize to novel situations depends on the capacity of this model.

While DMPs generate deterministic trajectories, Probabilistic Movement Primitives (ProMPs) [20] can encode a distribution of trajectories and generate stochastic policies. They can also learn linear relationship between environment variables and complex trajectories. Furthermore, given expert trajectories, ProMPs can generate new trajectories if conditioned for different trajectory points even if those points are outside the demonstration ranges. Therefore, we will compare our method with the generalization capabilities of ProMPs in this paper.

[21] investigated the generalization capabilities of DMPs given new task constraints. After learning from expert demonstrations, the confidence about the solution for new task constraints is calculated using Gaussian Processes and the agent asks expert to provide a new demonstration if confidence is below a threshold. Instead of requesting expert trajectories in case the confidence is low, it is desirable to discover the trajectories as addressed in our work. Instead of providing expert trajectory that might be very complex for the failed situations, we aim to provide either a reward specific to the task or important relevant points in the motion trajectory of the robot, and let the robot autonomously find the required motion trajectory through Reinforcement Learning. Therefore, we provide an overview of RL approaches in the next subsection.

B. Adapting Primitives

Learning from limited samples is an important challenge for reinforcement learning and unifying learning from demonstration with reinforcement learning is a popular approach to overcome this challenge. [9]. Most algorithms use expert demonstrations to bootstrap the agent to avoid random exploration at the beginning of training by filling replay buffer with these demonstrations. After a while, new experiences start to fill the buffer and expert demonstrations are omitted [22], [23]. It can be interpreted such that the starting point of the exploration is determined by expert demonstrations. Then RL agent explores the state and action space to achieve a more robust policy. In our work, we also start exploration from expert trajectories, however different from most of the approaches, the capability of generating expert trajectories are preserved while adapting to new constraints through reinforcement learning. In [22], the exploration of the agent is guided by expert demonstrations by defining an additional loss that measures the difference between the action of the agent and the demonstrated one. In this setting, the objectives are combined with a trade-off between two loss terms and how this trade-off is handled depends on a hyper-parameter set as the coefficient of this additional loss-term.
On the other hand, we let our policy network to learn different objectives by training the network for the 2 objectives at the same time.

Another approach, which tries to make RL agent policy to look like expert trajectory is GAIL (Generative Adverserial Imitation Learning). Here, a discriminator network is used to distinguish expert trajectories from produced trajectories and RL agent acts as a generator and tries to fool the discriminator by producing trajectories which has expert properties. However, training a Generative Adverserial Network is difficult on its own and for our task, diminished gradient is likely to happen where we want our agent to solve an objective which is not covered by experts. The discriminator network can easily distinguish trajectories since produced trajectory will be far away from expert trajectories and the generator won’t be able to show any progress and will receive negative reward no matter what is produces.

The motion trajectories found by RL can be added back to the expert trajectory dataset of the policies. Adding new trajectories into data-set is explored in imitation learning [24], however different from our RL-based approach, sampling from trajectory space and complete supervised learning was applied. In our approach, we simultaneously applied reinforcement learning and supervised learning and obtained stable solutions due to the robust and powerful underlying movement primitive representation, CNMPs.

### III. Method

Our framework enables a robot to learn a skill from expert demonstrations using CNMPs, and to adapt the learned skill to new constraints, i.e. regions outside the demonstrations via reinforcement learning. After providing background information on CNMPs and reinforcement learning, the proposed ACNMPs will be described in detail.

#### A. Background: Learning from Demonstration with CNMPs

CNMPs encode multi-modal sensorimotor temporal distribution of provided demonstrations and allow conditioning this distribution on any set of modalities at any time point. Fig. 1, from left to right, shows the training procedure of a CNMP using a hypothetical 1D scenario. In each training iteration, a changing number of random sensorimotor and time value couples are sampled from a uniformly random selected demonstration. These points are called observation points. The observation points are passed through the parameter sharing encoder network in order to be transformed into their latent space representations. These representations are then merged into one single general representation by using a symmetric operator which is usually defined as an averaging operation in practice. The produced general representation is concatenated with the target query time value and passed through a decoder network that produces a mean and variance. CNMP tries to predict the corresponding sensorimotor value distribution of that time-step based on the sampled observations. The network is trained end-to-end with stochastic gradient descent algorithm via the loss function:

\[
\mathcal{L}(\theta, \phi) = -\log P(SM(t_q) | \mu_q, \text{softplus}(\sigma_q))
\]

where \(\mu_q\) and \(\sigma_q\) are predicted distribution parameters over queried time-step \(t_q\), and \(SM(t_q)\) is the recorded sensorimotor value at queried time for the randomly selected demonstration in that training iteration.

After training, the CNMP can be conditioned on multiple and/or any time-steps in order to generate a trajectory distribution that satisfies the given conditions (Fig. 1, III). The whole trajectory can be generated by querying the all time-steps with the given conditions in order to predict the mean and variance values of the trajectory for each time-step. Generated trajectory can be used as an input to any robot controller to execute the motion.

#### B. Background: Policy Gradient RL

The behavior of RL agent is governed by the policy \(\pi_{\theta}(a,s) = \text{Pr}(a_t \in A | s_t \in S, \theta)\). \(S\) and \(A\) denote state and actions spaces, and \(\theta\) indicates the parameters of a function approximator. One can also generalize the policy to depend on a context or an external signal, \(c\), so that the policy can be written as \(\pi_{\theta}(a,s,c)\) or simply \(\pi(a,s,c)\). The agent has no control on \(c\); however it can affect the state \(s\) transitions by the actions \(a\) it takes.
We design our agent to generate signals based on time, thus time plays the role of context. Furthermore, as for our agent there is no natural state that it can affect, it becomes practically a generalized multi-armed bandit that has to learn a probability distribution parameterized by $c$, i.e., time.

As our agent needs to generate continuous actions, we adopt a policy gradient based algorithm for our agent. Policy gradient algorithms aim to increase the expected discounted total reward over a (state, action) trajectories $(\tau)$ by maximizing the expected reward $E_{\tau \sim \pi_\theta(\tau)}[R(\tau)]$ with respect to policy parameters $(\theta)$, where $R(\tau) = \sum_{t=1}^{T} R(s_t, a_t, c_t)$. It can be shown that the required gradient update on $\theta$ to achieve this is given by:

$$\nabla_{\theta} J(\theta) = E_{\pi_\theta}[(\sum_{t=1}^{T} \nabla_{\theta} \log \pi_\theta(s_t, a_t, c_t))(\sum_{t=1}^{T} R(s_t, a_t, c_t))]$$

(2)

In the case of our problem this simplifies to:

$$\nabla_{\theta} J(\theta) = E_{\pi_\theta}[(\sum_{t=1}^{T} \nabla_{\theta} \log \pi_\theta(a_t, c_t))(\sum_{t=1}^{T} R(a_t, c_t))]$$

(3)

C. Proposed Method

We extend the Conditional Neural Movement Primitives framework into a new system, so that it can perform beyond what is possible with the original CNMP learning by demonstration mechanism. This improvement is obtained by the introduction of a reinforcement learning agent that searches for trajectories to be fed to CNMP learning data set. The RL agent learns by tuning the weights of the trajectory decoding network (which is transferred form CNMP) so as to follow the policy gradient.

Fig. 2 provides the general framework. The setup we envision for the proposed model is a learning by demonstration setup, where a fixed amount of demonstration trajectories are provided and learned by CNMP; but yet the task requirements ask for extrapolation, or additional modifications on the reproduced trajectories based on limited feedback. Accordingly, at the onset, we assume that a CNMP model is trained with a set of expert demonstrations (Fig. 2(I)). A CNMP consists of encoder and decoder layers. Encoder layer facilitates the formation of representations of trajectory points (or other variables) conditioned on time. The decoder layer takes the learned representations and outputs the mean and variance of a Gaussian distribution as a function of time. Thus, given a time vector and the required condition, the decoder layer generates a sampled trajectory (Fig. 2(II)) with mean and variance information. Generated trajectory may not be useful for the task at hand when the network is asked to extrapolate beyond the demonstration set, or the asked trajectories are not well covered by the expert demonstration.

When the task failure occurs (Fig. 2(III-IV)), the execution of the action stops and the improvement algorithm takes over. RL agent finds a new trajectory (Fig. 2(V)) that satisfies the task constraints and this trajectory is added to the data-set of CNMP (Fig. 2(VI)).

Simultaneous Training with SL and RL: A crucial aspect of our framework is that while applying reinforcement learning for adapting to new constraints, it simultaneously continues being trained with the expert trajectories via supervised learning in order to preserve the learned knowledge. This ensures finding a model that not only produces novel trajectories that satisfy the new constraints but also reproduce previously learned trajectories. In practice, this allows the system to generate novel trajectories that share similar characteristics with the demonstrated ones.

In order to generate a new trajectory that both resembles the expert trajectories and acquires high reward, the agent is trained for 2 objectives. However, if we manipulate the CNMP loss in equation 1, it can be seen that it is similar to policy gradient loss:

$$\nabla_{\theta} J(\theta) = E_{CNMP_c}[(\sum_{t=1}^{T} \nabla_{\theta} \log_{CNMP_c}(s_t, a_t, c_t))]$$

(4)

For mean and variance of CNMP distribution, observations along with time can be written $(s_t, c_t)$, since they are mapped by neural networks. Expectation can be added because it will show the characteristics of mean and variance eventually. The only difference is the reward term because the true output is known and the reward is not needed to direct the agent.

Assimilating new RL solution into the CNMP: In finding the new solution, RL agent only considers the rewarding aspects of the trajectory; and therefore updates the underlying CNMP based on those points only. In order to fully assimilate the found solution into the CNMP, which is trained with all the points on given trajectories, RL solution is regarded as the new expert trajectory and added to the trajectory dataset. Finally, CNMP is re-trained with all trajectories in the dataset via supervised learning through sampling random points from these trajectories as described in Section A. This assimilation step ensures the capability to condition CNMP from any point in the range of previous expert demonstrations and newly found RL solutions.

D. Off-policy training

The RL agent is trained off-policy using the Retrace algorithm to increase the sample efficiency[25]. In the policy gradient equation (2) the expectation is taken for the current policy and the algorithm finds a new trajectory for each gradient update. Therefore, a trajectory is needed for every update. Instead, we can use the policy to update the network as much as we can. If we denote $\pi_{old}(a, c)$ for the policy, that we are using for update, the objective changes as follows.

2For rapid convergence and having the RL agent explore solutions in the neighborhood of the demonstrated trajectories, the RL agent uses a copy of the CNMP decoder layer as its policy network. Although, it is possible to train the CNMP encoder with the RL decoder as well, our empirical observation indicate that it is better to keep it fixed, and thus not to change the latent representation during policy gradient updates.
As it is suggested in [25] we use the clipping algorithm on importance sampling as \( \min(1, \pi(a_t, c_t)/\pi_{\text{old}}(a_t, c_t)) \) to avoid variance explosion. When the policies are too different, a KL divergence threshold \( D_{KL}(\pi(a, c) || \pi_{\text{old}}(a, c)) \) is defined between two distributions to get the new sample.

IV. Experimental Results

The performance of our system is evaluated in one 2D simulation and two real robot experiments. The first 2D obstacle avoidance experiment shows the capabilities of ACNMPs compared to CNMPs and ProMPs in adapting to trajectory constraints that were outside the range of the previously learned constraints. The second experiment shows that ACNMPs can adapt to non-linear relationships between task parameters and motion trajectories. Finally, the third experiment validates ACNMPs in a real-world pouring task.

A. Extrapolation in 2D Obstacle Avoidance

In this section, the capabilities of our model are investigated via hand-designed simulation trajectories, and results are compared to the two recent state-of-the-art LfD methods, namely, probabilistic movement primitives (ProMP) and the original version of the CNMP as we defined them as our baseline models.

In this experiment, we simulated an obstacle avoidance task in 2D world where different trajectories are given as demonstrations that avoid static obstacles. The aim of this experiment is to first verify that original CNMP formulation fails to generalize when conditioned with points outside the learning range and then to evaluate the effectiveness of our proposed method. The six demonstrations that start from the same position and end at different positions are shown in Fig. 3(a) with different colors. Given a different via-point (shown with a black dot), a trajectory whose shape is similar to the demonstrated ones is expected to be generated. However, after trained with the six demonstrations and conditioned with the black dot, CNMP generates a disparate trajectory that does not pass through the conditioned point as the conditioning was outside the training range, as shown in Fig. 3(b).

In order to adapt the primitive for the extrapolation point, we applied our proposed method that simultaneously adapts CNMP weights using previous demonstrations via supervised learning and the rewards computed based on distance between the generated and the conditioned points (shown with black dots) via RL. After approximately 35 number of roll-outs, our method is shown to generate a trajectory that passes through the given black-dots while preserving the shape similar to initial demonstrations as shown in Fig. 3(b). Note that, when only RL is applied on the learned CNMP, the system can also generate a trajectory that passes through the required point, however without preserving the shape Fig. 3(c).

Another widely used method that encodes distribution of the demonstrations, namely ProMP[20], was compared in learning and generalization of this 2d simulated obstacle avoidance task. ProMP was trained with 31 basis functions. As shown in Fig. 4 top-left plot, when a single condition is defined, ProMPs can directly generate a successful trajectory that passes through the given black-dots while preserving the shape similar to initial demonstrations as shown in Fig. 3(b). However, when conditioned with more points (top-right), ProMPs fail to generate a trajectory that goes through both points. This is probably because ProMPs cannot represent the required non-linear relationship that appeared around the third condition. While the original CNMP also fails in both extrapolation

\[
\nabla_\theta J(\theta) = \mathbb{E}_{\pi_{\text{old}}}(\sum_{t=1}^{T} \pi(a_t, c_t) / \pi_{\text{old}}(a_t, c_t)) \nabla_\theta \log \pi_{\text{old}}(a_t, c_t) R(\tau)
\]
Fig. 3: (a) The simulated 2d obstacle avoidance task. The 6 colored trajectories correspond to the demonstrated trajectories, the gray ellipses represent the underlying hypothetical obstacles and the pink red point shows the conditioned point. (b) CNMP fails to extrapolate. (c) Only RL based CNMP trajectory. (d) ACNMP: Simultaneous RL&SL based CNMP.

Assimilating new constraints into CNMP representations:

We further investigate how different demonstrations are encoded in the representation layer of CNMP and how this representation changed after reinforcement learning. In order to visualize the activation in the representation layer, the 128-dimensional representation space is reduced to a 2-dimensional latent space. Fig. 5 shows points sampled from the trajectories and their 2-D positions in the latent space. As shown, each separate trajectory is represented in a different cluster in the latent space. After RL is applied and the new found trajectory is integrated into the CNMP, it is represented in a separate cluster in the latent space. Note that, if the same activation were used in the latent space before RL step, the reproduced trajectory could not satisfy the constraints (as shown in top-right plot). This analysis shows that our method enables robust integration of new constraints into the existing representations.

Extreme Extrapolation:

In this analysis we investigate to what extent our algorithm successful is by placing the extrapolation point further away from the demonstrations. Although the algorithm still attempt finds solutions that satisfy the constraints, the shapes of the generated trajectories change significantly (see Fig. 6). Note that given only one constraint, “what must the right shape of the complete trajectory be?”
is not a well-defined question.

B. Extrapolation in real-robot control

This experiment investigates the capability of the ACNMP in extrapolating to conditions in an object pick and place task that requires obstacle avoidance. It includes a 6 degrees-of-freedom UR10 robotic arm equipped with a Robotiq gripper and a wrist mounted force/torque sensor. UR10 robotic arm equipped with aRobotiq gripper and a wrist mounted force/torque sensor was used for this purpose. The task was composed of moving the gripper to a suitable position to pick up the object according to its height first, and then moving it towards the target position following an arc avoiding the obstacle. ACNMP was initially trained with 8 movement trajectories that were obtained indifferent object-obstacle configurations. The heights of the object and obstacle were provided as parameters: 2.6 cm, 2.4, 6.8 cm. Original CNMP was previously shown [10] that the original CNMP fails to extrapolate to environments with lego blocks higher than the demonstrated ones. In this experiment, we trained ACNMP for lego blocks of heights 8 and 11 cm and showed that the system is able to generate the required joint trajectories at the end. The demonstrations, required trajectories for the novel lego heights and the generated trajectories are provided in Fig. 7 with black, blue and red lines, respectively; and snapshots from the successful execution of the robot is provided in Fig. 8. The average accuracy errors between the required and generated joint angles are provided in Table 1.

C. Extrapolating motion trajectories based on task parameters

In previous experiments, the extrapolation capability of ACNMPs are verified when it is conditioned in a novel point in its movement trajectory. The aim of this experiment is to show that ACNMPs can also adapt being conditioned to task parameters that are outside the range of training. The experimental setup is follows: The robot is given a cup that includes different amounts of marbles with the aim to pour the given amount into another cup. Depending on the weight of the cup in robot’s hand and required pouring amount, the robot should be able to generate wrist joint trajectories that enables suitable amount of rotation. Therefore, ACNMPs need to learn generating joint trajectories conditioned with initial weight of the cup and desired pouring amount.

For training, 16 expert joint trajectories were given with initial cup weights in the range of 650-1200 grams and rotation angles in the range of 85-95 degrees. After training, ACNMP is expected to generate trajectories for cups heavier than 1200 gram and outside the range of demonstrated pouring amounts, possibly with rotations higher than 95 degrees. Given the extrapolation parameter, 1400 gram initial cup weight and 1322 grams pouring amount, ACNMP found an RL solution and assimilated it into the primitive after 18 roll-outs. The learning progress of the RL agent is provided in Table 1. While the original CNMP model faces 600 gram error on this extrapolation tasks, ACNMP error rate dropped to 14 grams after training. Fig. 9 provides snapshots from

| Method | Parameters | Elbow | Wrist1 | Wrist2 |
|--------|------------|-------|--------|--------|
| CNMP   | Obj: 7 cm, Obs: 9° | 0.719 | 0.695 | 0.669 | 0.687 | 0.136 | 0.064 |
| CNMP + RL | Obj: 7 cm, Obs: 9° | 0.642 | 0.688 | 0.704 | 0.592 | 0.831 | 0.848 |
| CNMP   | Obj: 8 cm, Obs: 10° | 0.108 | 0.325 | 0.367 | 0.094 | 0.960 | 0.847 |
| CNMP + RL | Obj: 8 cm, Obs: 10° | 0.859 | 1.089 | 1.468 | 1.465 | 0.245 | 0.364 |
| CNMP   | Obj: 9 cm, Obs: 11° | 0.961 | 0.920 | 17.072 | 14.804 | 0.590 | 1.406 |
| CNMP + RL | Obj: 9 cm, Obs: 11° | 0.969 | 0.961 | 17.756 | 16.577 | 0.523 | 1.387 |
the successful extrapolation pouring task.

ACKNOWLEDGMENT

This research has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement no. 731761, IMAGINE.

REFERENCES

[1] B. D. Argall, S. Chernova, M. Veloso, and B. Browning, “A survey of robot learning from demonstration,” Rob. and Auto. Sys., vol. 57, no. 5, pp. 469–483, 2009.
[2] S. Schaal, “Is imitation learning the route to humanoid robots?” Trends in Cognitive Science, vol. 3, no. 6, pp. 233–242, 1999.
[3] C. G. Atkeson and S. Schaal, “Memory-based neural networks for robot learning,” Neurocomputing, vol. 9, no. 3, pp. 243–269, 1995. [Online]. Available: [Goto ISI:
[4] L. Peternel, T. Petric, E. Oztop, and J. Babic, “Teaching robots to cooperate with humans in dynamic manipulation tasks based on multi-modal human-in-the-loop approach,” Autonomous Robots, vol. 36, no. 1-2, pp. 123–136, 2014. [Online]. Available: [Goto ISI:
[5] J. Kober, A. Wilhelm, E. Oztop, and J. Peters, “Reinforcement learning to adjust parametrized motor primitives to new situations,” Autonomous Robots, vol. 33, no. 4, pp. 361–379, 2012.
[6] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, G. Ostrovski, et al., “Human-level control through deep reinforcement learning,” Nature, vol. 518, no. 7540, pp. 529–533, 2015.
[7] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. Van Den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, et al., “Mastering the game of go with deep neural networks and tree search,” nature, vol. 529, no. 7587, p. 484, 2016.
[8] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra, “Continuous control with deep reinforcement learning,” arXiv preprint arXiv:1509.02971, 2015.
[9] G. Dulac-Arnold, D. Mankowitz, and T. Hester, “Challenges of real-world reinforcement learning,” arXiv preprint arXiv:1904.12901, 2019.
[10] M. Y. Seker, M. Imre, J. Piater, and E. Ugru, “Conditional neural movement primitives,” in Robotics: Science and Systems (RSS), 2019.
[11] S. Calinon, P. Evrard, E. Gribovskaya, A. Billard, and A. Kheddar, “Learning collaborative manipulation tasks by demonstration using a haptic interface,” in Advanced Robotics, 2009. ICAR 2009. International Conference on. IEEE, 2009, pp. 1–6.
[12] T. Asfour, P. Azad, F. Gyargas, and R. Dillmann, “Imitation learning of dual-arm manipulation tasks in humanoid robots,” International Journal of Humanoid Robotics, vol. 5, no. 02, pp. 183–202, 2008.
[13] H. Ben Amor, O. Kroemer, U. Hillenbrand, G. Neumann, and J. Peters, “Generalization of human grasping for multi-fingered robot hands,” in IROS. IEEE, 2012, pp. 2043–2050.