Learning Deformable Manipulation from Expert Demonstrations

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Abstract—We present a novel Learning from Demonstration (LfD) method, Deformable Manipulation from Demonstrations (DMfD), to solve deformable manipulation tasks using states or images as inputs, given expert demonstrations. Our method uses demonstrations in three different ways, and balances the trade-off between exploring the environment online and using guidance from experts to explore high dimensional spaces effectively. We test DMfD on a set of representative manipulation tasks for a 1-dimensional rope and a 2-dimensional cloth from the SoftGym suite of tasks, each with state and image observations. Our method exceeds baseline performance by up to 12.9% for state-based tasks and up to 33.44% on image-based tasks, with comparable or better robustness to randomness. Also, we create two challenging environments for folding a 2D cloth using image-based observations, and set a performance benchmark for them. We deploy DMfD on a real robot (sim2real gap ~6%).

I. INTRODUCTION

Autonomous dexterous robotic manipulation is challenging. For rigid objects, challenges include estimating pose and mass distribution, grasp prediction, and real world grasp planning. Obtaining the state and dynamics for deformable objects is much harder than for rigid objects. Even with ‘full’ state information, deformable manipulation is very high dimensional, making it more challenging than rigid manipulation [1].

Our method, Deformable Manipulation from Demonstrations (DMfD), is a learned agent for deformable manipulation using expert data three ways. We leverage an advantage-weighted formulation [2], [3] in the loss function, with expert samples (pre-populated in the replay buffer) appropriately weighted to encourage the policy to mimic expert actions. Finally, during experience collection, we use reference state initialization [4], where the agent is reset along an expert trajectory with some probability. We then compare the state trajectories of the expert and agent, helping exploration in difficult to reach states. Fig. 1 shows rollouts of our method for challenging image-based manipulation tasks.

Contributions: We propose a novel method (DMfD) for a learning agent to absorb expert guidance (from human execution or hand-engineered methods), while learning to solve challenging deformable manipulation tasks online.

- DMfD solves deformable manipulation tasks for state and image based observations using expert data in three ways. Our online training loss formulation balances exploring online and mimicking experts.

II. BACKGROUND

Autonomous deformable manipulation is a challenge with many real-world applications such as folding clothes, cooking, or assisting humans [6]–[9]. Analytical methods such as Finite Element Method [10] and Material-Point Methods [11] are used to model object dynamics. Control methods such as trajectory optimization [12]–[15] and model predictive control [16] are used to manipulate objects. However, they might not generalize to environment variations. Data-driven methods are popular for manipulation tasks [17], including Imitation Learning (IL) [18]–[23], Reinforcement Learning (RL) [24]–[28], and their combination [29]–[32]. However, most successes have been in rigid body manipulation.

Here, we focus on deformable object manipulation using expert-guided RL. Learning from expert Demonstrations (LfD) has been applied to deformable manipulation tasks like bed making [33] and manipulating beads, clothes, and bags [34]. Reinforcement learning has been applied to manipulation of ropes, clothes, and liquids [5], [35], sometimes with vision [7], [36]–[40]. Combining RL with LfD can balance expert guidance with online exploration [29]–[31]. Deep Mimic [4] uses Reference State Initialization (RSI) to initialize from high-value states, mitigating such exploration costs. Advantage
requiring the policy to minimize an entropy loss term, 

$$\mathcal{L}_p = (1 - w_E) \mathcal{L}_A + w_E \mathcal{L}_E, \quad 0 \leq w_E \leq 1$$  \hfill (3)$$

While collecting experience, we reset the robot to an expert’s state with probability $p_B$, and compare the agent’s generated trajectory to the expert’s, giving an imitation reward. This reference state initialisation (RSI) was introduced in DeepMimic [4] to help explore hard to reach high-dimensional states. Our method uses this idea to help mimic the expert during the initial stages of training.

Our actor and critic networks have hidden layers with tanh activation. A Convolutional Neural Network (CNN) encoder and random image crops [37] are added for image-based training. Fig. 2 shows these architectures. Note the critic also gets state input in addition to the observation. This privileged information helps stabilize it [42].

IV. EXPERIMENTS

A. Tasks and Experimental Setup

We test on the tasks below with state or image observations as applicable. Object states are encoded with their object-specific reduced-state. Image observations are 32x32 RGB images showing the object and robot end-effector. Each task has a set of variants, where the deformable object’s properties vary for effective domain randomization.

1) Straighten Rope: Stretch the rope a fixed distance apart, to straighten it. The reduced state is the $(x, y, z)$ coordinates of 10 equidistant points including rope ends.
2) Cloth Fold: Fold a flattened cloth into half, along an edge, using two end-effectors. The reduced state is the $(x, y, z)$ coordinates of each corner.
3) Cloth Fold Diagonal Pinned (Unpinned): Fold the square cloth along a specified diagonal, with a single end-effector, and one corner pinned (unpinned). The reduced state is the $(x, y, z)$ coordinates of each corner.

These are two new tasks we introduce.

Image-based environments are more difficult to solve than state-based environments. Hence, we focused on image inputs for the two novel Cloth Fold Diagonal tasks. This gives 6 test environments: 4 from SoftGym (state and image inputs for Straighten Rope and Cloth Fold) and 2 new tasks (image inputs for Cloth Fold Diagonal). Demonstrations are hand-coded for variants $v \subseteq \mathcal{V}$, using full state and dynamics.

We use normalized performance in $[0, 1]$ from SoftGym,

$$\hat{p}(t) = \frac{p(s_t) - p(s_0)}{p_{opt} - p(s_0)}$$  \hfill (4)$$

where $p(s_t)$ is the env-specific performance at state $s_t$ at time $t$, and $p_{opt}$ is the best possible performance. As in SoftGym, we compare performance at the end of the episode, $\hat{p}(H)$.

B. Performance Comparisons

We compare our method with LfD baselines AWAC [3], BC [20], SAC-LfD (SAC with pre-populated expert data in the replay buffer), and SAC-BC (SAC with initialized actor networks from pre-trained BC-Image on expert demonstrations). We also compare with non-LfD baselines SAC, SAC-CURL [36], and DrQ [37].
Fig. 3: State-of-the-art comparisons. Learning curves of normalized performance $\bar{H}$ for all environments during training, until convergence. The first column (a & b) shows SoftGym state-based environments. The second column (d & e) show SoftGym image-based environments, and the third column (c & f) show our new Cloth Fold Diagonal environments. State-based DMfD is light blue, image-based agent is dark blue, and expert performance is black. Behavioural Cloning does not train online; its results are shown as constant gray line. The means $\mu$ are plotted as solid lines, and one standard deviation $(\mu \pm \sigma)$ is the shaded region. We find that DMfD consistently beats the baselines, with comparable or better variance.

Fig. 3 shows the training curves of our method against baselines for all environments. As the environments increase in difficulty, our method outperforms baselines by increased margins for state-base and image-based environments.

C. Discussion

When comparing with experts, Fig. 3 shows that our state-based agents beat the oracle in both state environments. However, the image-based agents are, at best, comparable to the expert, since they do not have privileged state information.

We see the performance gap between DMfD and baselines increase with task difficulty. In a hard task like Cloth Fold Image (Fig. 3c), baselines perform at or below 0 after training.

State-based environments: DMfD’s multiple uses of expert data is one main reason why it performs better than SAC, which does not use expert data. This significantly affects performance on hard state-based tasks like Cloth Fold.

Conversely, AWAC can achieve better performance on difficult tasks with expert data. However, no entropy regularization causes AWAC’s vulnerability to reach local optiums in training, causing its higher variance than DMfD and lower robustness to randomness. As seen in Fig. 3a, high variance after 1M steps leads to its performance deteriorating.

Image-based environments are harder to solve, and our method outperforms the baselines even further. Our critic is privileged with state data, helping it estimate the value function better. The use of expert data, with the exploration due to entropy regularization, helps our method outperform baselines with comparable or better variance.

Although the baselines have state-of-the-art methods for learning with vision, only the LfD baselines incorporate expert demonstrations, such as BC. In fact, BC outperforms CuRL and DrQ in some environments despite training offline. BC however has drawbacks such as covariate shift and sensitivity to environmental changes. Fig. 3c and Fig. 3f show very different BC performance between the Pinned and Unpinned Cloth Fold Diagonal tasks, even though they are similar. Additionally, BC cannot exceed the expert performance.

Our experiments show DMfD matches or outperforms baselines across environments, and is robust to noise.

V. Conclusion

Deformable Manipulation from Demonstrations (DMfD) is a novel method leveraging expert demonstrations and outperforms state-of-the-art LfD methods for deformable manipulation tasks. We demonstrate the effectiveness of our method on six tasks, including two new challenging cloth folding tasks we created. We show a consistent and significant performance improvement over baselines in state-based environments (up to 12.9%) and an even higher improvement on tougher image-based environments (up to 33.44%). We observe comparable or lower variance than the baselines, indicating higher robustness to noise. Finally, we conducted real robot experiments and achieved a minimal sim2real gap (~6%).
REFERENCES


