Learning to Manipulate Deformable Objects without Demonstrations

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Abstract—In this paper we tackle the problem of deformable object manipulation through model-free visual reinforcement learning (RL). In order to circumvent the sample inefficiency of RL, we propose two key ideas that accelerate learning. First, we propose an iterative pick-place action space that encodes the conditional relationship between picking and placing on deformable objects. The explicit structural encoding enables faster learning under complex object dynamics. Second, instead of jointly learning both the pick and the place locations, we only explicitly learn the placing policy conditioned on random pick points. Then, by selecting the pick point that has Maximal Value under Placing (MVP), we obtain our picking policy. Using this learning framework, we obtain an order of magnitude faster learning compared to independent action-spaces on our suite of deformable object manipulation tasks. Finally, using domain randomization, we transfer our policies to a real PR2 robot for challenging cloth and rope manipulation.

I. INTRODUCTION

Over the last few decades, we have seen tremendous progress in robotic manipulation. From grasping objects in clutter [1]–[5] to dexterous in-hand manipulation of objects [6], [7], modern robotic algorithms have transformed object manipulation. But much of this success has come at the price of making a key assumption: rigidity of objects. Most robot algorithms often require (implicitly or explicitly) strict rigidity constraints on objects. But the objects we interact with everyday, from the clothes we put on to shopping bags we pack, are deformable. In fact, even ‘rigid’ objects deform under different shape factors (like a metal wire). Because of this departure from the ‘rigid-body’ assumption, several real-world applications of manipulation fail [8]. So why haven’t we created equally powerful algorithms for deformable objects yet?

Deformable object manipulation has been a long standing problem [9]–[13], with two unique challenges. First, in contrast with rigid objects, there is no obvious representation of state. Consider the cloth manipulation problem in Fig. 1(a). How do we track the shape of the cloth? Should we use a raw point cloud, or fit a continuous function? This lack of canonical state often limits state representations to discrete approximations [14]. Second, the dynamics is complex and non-linear [15]. Due to microscopic interactions in the object, even simple looking objects can exhibit complex and unpredictable behavior [16]. This makes it difficult to model and perform traditional task and motion planning.

One of the recent breakthroughs in robotics has been the development of model-free visual policy learning [6], [17], [18], where robotic algorithms can reason about interactions directly from raw sensory observations. This can alleviate the challenge of state estimation for deformable objects [19], since we can directly learn on images. Moreover, since these methods do not require an explicit model of the object [20], it can overcome the challenge of having complex deformable object dynamics. But model-free learning has notoriously poor sample complexity [21]. This has limited the application of learning to the setting where human demonstrations are available [19], [22]. In concurrent and independent work, [23] has shown how simulated demonstrators can be used to learn manipulation strategies to spread out a cloth.

In this work, we tackle the sample-complexity issue by focusing on an often ignored aspect of learning: the action space. Inspired by [24], [25], we start by using an iterative pick-place action space, where the robot can decide which point to grasp (or pick) and to which point it should drop (or place). But how should one learn with this action space?
One option is to directly output both the pick point and place location for the deformable object. But the optimal placing location is heavily correlated with picking location, i.e., where you place depends heavily on what point you pick. This conditional structure makes it difficult to simultaneously learn without modeling this aspect of the action space.

To solve this, we propose a conditional action space, where the output of the picking policy is fed as input into the placing policy. But this leads us to a second problem: the placing policy is constrained by the picking policy. When learning starts, the picking policy often collapses into a suboptimal restrictive set of pick points. This inhibits the exploration of the placing policy, since the picking points it takes as input are only from a restrictive set, and results in a suboptimal placing policy. Now, since the rewards for picking come after the placing is executed, the picking policy receives poor rewards and results in inefficient learning. This illustrates the chicken and egg problem with conditional action spaces. Learning a good picking strategy involves having a good placing strategy, while learning a good placing strategy involves having a good picking strategy.

To break this chicken and egg loop, we learn the placing strategy independent of the picking strategy. This allows us to both learn the placing policy efficiently, and use the learned placing value approximator [20] to inform the picking policy. More concretely, since the value of the placing policy is conditioned on the pick point, we can find the pick point that maximizes the value. We call this picking policy Maximum Value of Placing (MVP). During training, the placing policy is trained with a random picking policy. However, during testing, the MVP picking policy is used. Through this, we observe a significant speedup in convergence on three difficult deformable object manipulation tasks on rope and cloth objects. Finally, we demonstrate how this policy can be transferred from a simulator to a real robot using simple domain randomization without any additional real-world training or human demonstrations. Videos of our PR2 robot performing deformable object manipulation along with our code can be accessed on the project website: https://sites.google.com/view/alternating-pick-and-place.

In summary, we present three key contributions in this paper: (a) we propose a novel learning algorithm for picking based on the maximal value of placing; (b) we show that the conditional action space formulation significantly accelerates the learning for deformable object manipulation; and (c) we demonstrate transfer to real-robot cloth and rope manipulation.

II. RELATED WORK

A. Deformable Object Manipulation

Robotic manipulation of deformable objects has had a rich history that has spanned different fields from surgical robotics to industrial manipulation. For a more detailed survey, we refer the reader to [10], [26].

Motion planning has been a popular approach to tackle this problem, where several works combine deformable object simulations with efficient planning [27]. Early work [28]–[30] focused on using planning for linearly deformable objects like ropes. [31] developed methods for fully deformable simulation environments, while [32] created methods for faster planning with deformable environments. One of the challenges of planning with deformable objects, is the large degrees of freedom and hence large configuration space involved when planning. This, coupled with the complex dynamics [15], has prompted work in using high-level planners or demonstrations and local controllers to follow the plans.

Instead of planning on the full complex dynamics, we can plan on simpler approximations, but use local controllers to handle the actual complex dynamics. One way to use local controllers is model-based servoing [9], [33], where the end-effector is locally controlled to a given goal location instead of explicit planning. However, since the controllers are optimized over simpler dynamics, they often get stuck in local minima with more complex dynamics [34]. To solve this model-based dependency, several works [14], [35], [36] have looked at Jacobian approximated controllers that do not need explicit models, while [37], [38] have looked at learning-based techniques for servoing. However, since the controllers are still local in nature, they are still susceptible to reaching globally suboptimal policies. To address this, [34] interleaves planning along with local controllers. Although this produces better behavior, transferring it to a robot involves solving the difficult state-estimation problem [39], [40]. Instead of a two step planner and local controller, we propose to directly use model-free visual learning, which should alleviate the state-estimation problem along with working with the true complex dynamics of the manipulated objects.

B. Reinforcement Learning for Manipulation

Reinforcement Learning (RL) has made significant progress in many areas such as robotics. RL has enabled robots to handle unstructured perception such as visual inputs and reason about actions directly from raw observations [41]. It has been shown to solve manipulation problems such as in-hand block manipulation [6], [42], object pushing [43], and valve-rotating with a three-fingered hand [44]. However, these algorithms have not yet seen wide applicability to deformable object manipulation. This is primarily due to learning being inefficient with complex dynamics [21], which we address in this work.

Over the last few years, deformable object manipulation has also been studied in reinforcement learning [19], [22], [23], [45], [46]. However, many of these works [19], [45] require expert demonstrations to guide learning for cloth manipulation. These expert demonstrations can also be used to learn wire threading [47], [48]. In concurrent work, [23] shows that instead of human demonstrators, a simulated demonstrator using state information can be used to obtain demonstrations. Other works [22] that do not need demonstrations for training require them at test time. We note that since using our conditional action spaces and MVP technique can be applied to any actor-critic algorithm, it is
Before we describe our learning framework, we briefly discuss relevant background on reinforcement learning and off-policy learning. For a more in-depth survey, we refer the reader to [49], [50].

### A. Reinforcement Learning

We consider a continuous Markov Decision Process (MDP), represented by the tuple \((S, O, A, \mathcal{P}, r, \gamma, s_0)\), with continuous state and action space, \(S\) and \(A\), and a partial observation space \(O\). \(\mathcal{P} : S \times A \times S \rightarrow [0, \infty)\) defines the transition probability of the next state \(s_{t+1}\) given the current state-action pair \((s_t, a_t)\). For each transition, the environment generates a reward \(r : S \times A \rightarrow \mathcal{R}\), with future reward discounted by \(\gamma\).

Starting from an initial state \(s_0\) sampled from distribution \(S\), the agent takes actions according to policy \(\pi(a_t | s_t)\) and receives reward \(r_t = r(s_t, a_t)\) at every timestep \(t\). The next state \(s_{t+1}\) is sampled from the transition distribution \(\mathcal{P}(s_{t+1} | s_t, a_t)\). The objective in reinforcement learning is to learn a policy that maximizes the expected sum of discounted rewards \(\sum \mathbb{E}(s_{t+1}, a_{t+1}) \sim \mathcal{P}(s_{t+1}, a_{t+1}) [\gamma^t r(s_t, a_t)]\). In the case of a partially observable model, the agent receives observations \(o_t\) and learns \(\pi(a_t | o_t)\).

### B. Off Policy Learning

On-policy reinforcement learning [51]–[53] iterates between data collection and policy updates, hence requiring new on-policy data per iteration which tends to be expensive to obtain. On the other hand, off-policy reinforcement learning retains past experiences in a replay buffer and is able to re-use past samples. Thus, in practice, off-policy algorithms have achieved significantly better sample efficiency [44], [54]. Off-policy learning can be divided into three main categories: model-based RL, Actor-Critic (AC), and Q learning. In model-based RL, we learn the dynamics of the system. In the AC framework, we learn both the policy (actor) and value function (critic). Finally, in Q-learning we often learn only the value function, and choose actions that maximize it.

In this work, we consider the actor-critic framework since it is the most suitable for continuous control, as well as data-efficient and stable. Recent state-of-the-art actor-critic algorithms such as Twin Delayed DDPG (TD3) [55] and Soft-Actor-Critic (SAC) [56] show better performance than prior off-policy algorithms such Deep Deterministic Policy Gradient (DDPG) [57] and Asynchronous Advantage Actor-Critic (A3C) [58] due to variance reduction methods in TD3 by using a second critic network to reduce over-estimation of the value function and an additional entropy term in SAC to encourage exploration. In this work, we use SAC since its empirical performance surpasses TD3 (and other off-policy algorithms) on most RL benchmark environments [56]. However, our method is not tied to SAC and can work with any off-policy learning algorithm.

### IV. Approach

We now describe our learning framework for efficient deformable object manipulation. We start by the pick and place problem. Following this, we discuss our algorithm.

#### A. Deformable Object Manipulation as a Pick and Place Problem

We look at a more amenable action space while retaining the expressivity of the general action space: pick and place. The pick and place action space has had a rich history in planning with rigid objects [25], [59]. Here, the action space is the location to pick (or grasp) the object \(a_t^{\text{pick}}\) and the location to place (or drop) the object \(a_t^{\text{place}}\). This operation is done at every step \(t\), but we will drop the superscript for ease of reading. With rigid objects, the whole object hence moves according \(a_t \rightarrow a_t^{\text{place}}\). However, for a deformable object, only the point corresponding to \(a_t^{\text{pick}}\) on the object moves to \(a_t^{\text{place}}\), while the other points move according to the kinematics and dynamics of the deformable object [22]. Empirically, since in each action the robot picks and places a part of the deformable object, there is significant motion in the object, which means that the robot gets a more informative reward signal after each action. Also note that this setting allows for multiple pick-and-place operations that are necessary for tasks such as spreading out a scrunched up piece of cloth.

#### B. Learning with Composite Action Spaces

The straightforward approach to learning with a pick-place action space is to learn a policy \(\pi_{\text{joint}}\) that directly outputs the optimal locations to pick and to place \([a_t^{\text{pick}}, a_t^{\text{place}}]\), i.e., \(\pi_{\text{joint}} \equiv p(a_t^{\text{pick}} | o) \cdot p(a_t^{\text{place}} | o)\) where \(o\) is the observation of the deformable object (Fig. 2(a)). However, this approach fails to capture the underlying composite and conditional nature of the action space, where the location to place \(a_t^{\text{place}}\) is strongly dependent on the pick point \(a_t^{\text{pick}}\).

One way to learn with conditional output spaces is to explicitly factor the output space during learning. This has provided benefits in several other learning problems from generating images [60] to predicting large dimensional robotic actions [61], [62]. Hence instead of learning the joint policy, we factor the policy as:

\[
\pi_{\text{factor}} \equiv \pi_{\text{pick}}(a_t^{\text{pick}} | o) \cdot \pi_{\text{place}}(a_t^{\text{place}} | o, a_t^{\text{pick}}) \tag{1}
\]

This factorization will allow the policy to reason about the conditional dependence of placing on picking (Fig. 2(b)). However, in the context of RL, we face another challenge: action credit assignment. Using RL, the reward for a specific behavior comes through the cumulative discounted reward at the end of an episode. This results in the temporal credit assignment problem where attributing the reward to a specific action is difficult. With our factored action spaces, we now have an additional credit assignment problem on the different factors of the action space. This means that if an action receives high reward, we do not know if it is due to \(\pi_{\text{pick}}\) or \(\pi_{\text{place}}\). Due to this, training \(\pi_{\text{factor}}\) jointly is inefficient.
and often leads to the policy selecting a suboptimal pick location. This suboptimal $\pi_{\text{pick}}$ then does not allow $\pi_{\text{place}}$ to learn, since $\pi_{\text{place}}(a_{\text{place}}|a_{\text{pick}})$ only sees suboptimal picking locations $a_{\text{pick}}$ during early parts of training. Thus, this leads to a mode collapse as shown in Sec. V-D.

To overcome the action credit assignment problem, we propose a two-stage learning scheme. Here the key insight is that training a placing policy can be done given a full-support picking policy and the picking policy can be obtained from the placing policy by accessing the Value approximator for placing. Algorithmically, this is done by first training $\pi_{\text{place}}$ conditioned on picking actions from the uniform random distribution $U_{\text{pick}}$. Using SAC, we train and obtain $\pi_{\text{place}}(a_{\text{place}}|a_{\text{pick}})$, s.t. $a_{\text{pick}} \sim U_{\text{pick}}$ as well as the place value approximator $V_{\text{place}}(o,a_{\text{pick}})$. Since the value is also conditioned on pick point $a_{\text{pick}}$, we can use this to obtain our picking policy as:

$$\pi_{\text{pick}} \equiv \arg \max_{a_{\text{pick}}} V_{\text{place}}(o,a_{\text{pick}}) \quad (2)$$

We call this picking policy: Maximum Value under Placing (MVP). MVP allows us get an informed picking policy without having to explicitly train for picking. This makes training efficient for off-policy learning with conditional action spaces especially in the context of deformable object manipulation.

V. EXPERIMENTAL EVALUATION

In this section we analyze our method MVP across a suite of simulations and then demonstrate real-world deformable object manipulation using our learned policies.

A. Cloth Manipulation in Simulation

Most current RL environments like OpenAI Gym [63] and DM Control [64], offer a variety of rigid body manipulation tasks. However, they do not have environments for deformable objects. Therefore, for consistent analysis, we build our own simulated environments for deformable objects using the DM Control API. To simulate deformable objects, we use composite objects from MuJoCo 2.0 [65]. This allows us to create and render complex deformable objects like cloths and ropes. Using MVP, we train policies both on state (locations of the composite objects) and image observations ($64 \times 64 \times 3$ RGB). For image-based experiments, we uniformly randomly select a pick point on a binary segmentation of the cloth or rope in order to guarantee a pick point on the corresponding object.

The details for the three environments we use are as follows:

1. **Rope**: The goal is to stretch the rope (simulated as a 25 joint composite) horizontally straight in the center of the table. The action space is divided into two parts as $a_{\text{pick}}$ and $a_{\text{place}}$. $a_{\text{pick}}$ is the two dimension pick point on the rope, and $a_{\text{place}}$ is the relative distance to move and place the rope. All other parts of the rope move based on the simulator dynamics after each action is applied. The reward for this task is computed from the segmentation of the rope in RGB images as:

$$\text{reward} = \sum_{i=1}^{W} e^{0.5 \times |i-32|} \sum_{j=1}^{W} s_{i,j}, \quad (3)$$

where $i$ is the row number of the image, $j$ is the column number, and $s_{i,j}$ is the binary segmentation at pixel location $(i,j)$. Hence for a $64 \times 64$ image the reward encourages the rope to be in the center row (row number 32) with an exponential penalty on rows further from the center. At the start of each episode, the rope is initialized by applying a random action for the first 50 timesteps.

2. **Cloth-Simplified**: The cloth consists of an 81 joint composite that is a $9 \times 9$ grid. The robot needs to pick the corner joint of the cloth and move that to the target place. The action space is similar to the rope environment except the picking location can only be one of the four corners. In this environment, the goal is to flatten the cloth in the middle of the table. Our reward function is the intersection of the binary mask of the cloth or rope in RGB. For image-based experiments, we use a colormap [66] skin with four different colors in the corner.

3. **Cloth**: In contrast to the Cloth-Simplified environment that can only pick one of the 4 corners, Cloth allows picking any point in the pixel of cloth (if it is trained with image observation) or any composite particle (if state observation is used). The reward used is the same as in Cloth-Simplified. For both the Cloth and Cloth-Simplified environments, the
Fig. 3. Learning comparisons between baselines and our method on the three deformable object manipulation environments with state-based training in simulation. The dotted black line is computed by evaluating MVP using the most recently trained random pick policy. Each experiment was run on 4 random seeds.

Fig. 4. Learning comparisons between baselines and our method on two deformable object manipulation environments with image-based training in simulation. Note that we do not include the cloth-simplified environment here since image-based transfer to real robot would involve corner detection. The dotted black line is computed by evaluating MVP using the most recently trained learned placing with uniform pick policy. Each experiment was run on 3 random seeds.

cloth is initialized by applying a random action for the first 130 timesteps of each episode.

B. Learning Methods for Comparison

Fig. 3 and Fig. 4 show our experimental results for various model architectures on the rope and cloth environments. To understand the significance of our algorithm, we compare the following learning methods: random, independent, conditional, learned placing with uniform pick, and MVP (ours).

- **Random**: We sample actions uniformly from the pick-place action space of the robot.
- **Independent**: We use a joint factorization of $p(a_{\text{pick}}|o) \times p(a_{\text{place}}|o)$ by simultaneously outputting the $a_{\text{pick}}$ and $a_{\text{place}}$.
- **Conditional**: We first choose a pick location, and then choose a place vector distance given the pick location, modeled as $p(a_{\text{pick}}|o) \times p(a_{\text{place}}|a_{\text{pick}}, o)$.
- **Learned Placing with Uniform Pick**: We use the conditional distribution $p(a_{\text{place}}|a_{\text{pick}}, o)$, where $a_{\text{pick}}$ is uniformly sampled from the pick action space.
- **MVP (ours)**: We use the trained learned placing with uniform pick policy and choose $a_{\text{pick}}$ by maximizing over the learned Q-function.

C. Training Details

For the training in the simulation, we use SAC [44] as our off-policy algorithm and make a few modifications on the rlpyt code-base [67]. For state-based experiments, we use an MLP with 2 hidden layers of 256 units each; approximately 150k parameters. For image-based experiments, we use a CNN with 3 convolutions with channel sizes $(64, 64, 4)$, each with a kernel size of 3 and a stride of 2. This is followed by 2 fully connected hidden layers of 256 units each. In total approximately 200k parameters are learned. For all models, we repeat the pick information 50 times before concatenating with the state observations or flattened image embeddings. The horizon for Rope is 200 and 120 for both Cloth environments. The minimum replay pool size is 2000 for Rope and 1200 for the Cloth environments. The image size used for all environments is $64 \times 64 \times 3$. Based on the original code, we added parallel environment sampling to speed-up overall training by 3–5 times.
D. Does conditional pick-place learning help?

To understand the effects of our learning technique, we compare our learned placing with uniform pick technique with the independent representation in Fig. 3. We can see that using our proposed method shows significant improvement in learning speed for state-based cloth experiments, and image-based experiments in general. The state-based rope experiments do not show much of a difference due to the inherent simplicity of the tasks. Our method shows significantly higher rewards in the cloth simplified environment, and learns about 2X faster in the harder cloth environment. For image-based experiments, the baseline methods do no better than random while our method gives an order of magnitude (5-10X) higher performance for reward reached. The independent and conditional factored policies for image-based cloth spreading end up performing worse than random, suggesting some sort of mode collapse occurring [68]. This demonstrates that conditional learning indeed speeds up learning for deformable object manipulation especially when the observation is an image.

E. Does setting the picking policy based on MVP help?

One of the key contributions of this work is to use the placing value to inform the picking policy (Eq. 2) without explicitly training the picking policy. As we see in both state-based (Fig. 3) and image-based case (Fig. 4) training with MVP gives consistently better performance. Even when our conditional policies with uniform pick location fall below the baselines as seen in Cloth (State) and Rope (State), using MVP significantly improves the performance. Note that although MVP brings relatively smaller boosts in performance compared to the gains brought by the learned placing with uniform pick policy, we observe that the learned placing with uniform pick policy already achieves a high success rate on completing the task, and even a small boost in performance is visually substantial when running evaluations in simulation and on our real robot.

F. How do we transfer our policies to a real robot?

To transfer our policies to the real-robot, we use domain randomization (DR) [18], [62], [69] in the simulator along
with using images of real cloths. DR is performed on visual parameters (lighting and textures) as well physics (mass and joint friction) of the cloth. On our PR2 robot (Fig. 1(a)) we capture RGB images from a head-mounted camera and input the image into our policy learned in the simulator. Since $o_{\text{pick}}$ and $o_{\text{place}}$ are both defined as points on the image, we can easily command the robot to perform pick-place operations on the deformable object placed on the green table. Additionally, in simulation evaluation, we notice no degradation in performance due to DR while training using MVP (Fig. 6).

G. Evaluation on the real robot

We evaluate our policy on the rope-spread and cloth-spread experiments. As seen in Fig. 5, policies trained using MVP are successfully able to complete both spreading tasks. For our cloth spreading experiment, we also note that due to domain randomization, a single policy can spread cloths of different colors. For quantitative evaluations, we select 4 start configurations for the cloth and the rope and compare with various baselines (Table I) on the spread coverage metric. For the rope task, we run the policies for 20 steps, while for the much harder cloth task we run policies for 150 steps. The large gap between MVP trained policies and independent policies supports our hypothesis that the conditional structure is crucial for learning deformable object manipulation. Robot execution videos can be accessed from the project website: https://sites.google.com/view/alternating-pick-and-place.

VI. CONCLUSION AND FUTURE WORK

We have proposed a conditional learning approach for learning on manipulating deformable objects. We have shown this significantly improves sample complexity. To our knowledge, this is the first work that trains RL from scratch for deformable object manipulation and demonstrates it on real robot. This finding opens up many exciting avenues for deformable object manipulation from bubble wrapping a rigid object to folding a T-shirt, which pose additional challenges in specifying a reward function and handling partial observability. Additionally, since our technique only assumes an actor-critic algorithm, we believe it can be combined with existing learning from demonstration based techniques to obtain further improvements in performance.

VII. ACKNOWLEDGEMENTS

We thank AWS for computing resources and Boren Tsai for support in setting up the robot. We also gratefully acknowledge the support from Komatsu Ltd., The Open Philanthropy Project, Berkeley DeepDrive, NSF, and the ONR Pecase award.

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