Learning-Based Methods for General Robotic Manipulation

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1 Background and Context

Robots are widely used throughout modern society, but the vast majority of commercial robots today rely on either highly predictable environments or persistent human supervision. With no environment uncertainty, robots in manufacturing can be scripted to perform a task such as spot welding or assembly with extremely high precision and repeatability. In domains such as robot surgery, a human surgeon provides complete supervision by teleoperating the robot (Yip and Das, 2017). Outside of such settings, it remains an open question as to whether robots may be autonomously deployed in the real world while maintaining reliability, but successful approaches could have tremendous impact. For example, robots that can reliably manipulate objects may address bin-picking and recycling in warehouses, cleaning an environmental disaster site, or caring for an aging population. Since the real world presents an infinite supply of new data, the key criteria we require for robots is that they must *maintain reliability when generalizing to new configurations*.

Machine learning is a promising tool for generalization. In the last decade, there have been tremendous empirical advances of deep learning in image classification (Krizhevsky et al., 2012), as well as in interactive settings like reinforcement learning (RL) (Sutton and Barto, 2018), where an agent's actions influence the distribution of subsequent states it encounters. Robots face interactive settings across many domains ranging from a person's home to a company's warehouse, but many relevant algorithmic advances have been tested in simulation, particularly games (Mnih et al., 2015; Silver et al., 2016), where one can run algorithms with less regard towards issues such as sample efficiency, hardware damage, imprecision of physical robots, and safety of human operators or bystanders. While the robotics research community has shown potential for physical robots to learn tasks through learning-based methods (Levine et al., 2016; Mahler et al., 2019), many challenges remain before we can deploy autonomous robots in the real world.

2 Prior Research

My primary research objective is the development and application of learning-based techniques for robot manipulation. I apply these on manipulation tasks with highly deformable objects such as cables, fabrics, and bags. Deformable object manipulation is challenging because of dual difficulties in (1) modeling the object's configuration and (2) modeling the dynamics of deformables. I also investigate data-driven robot manipulation for surgical robots, with the goal of automating challenging surgical subtasks.

Manipulation of Fabrics with Machine Learning. In the early 2010s, approaches for fabric manipulation often used traditional computer vision algorithms such as corner detection for perception, and then leveraged geometric controllers (Maitin-Shepard et al., 2010; Doumanoglou et al., 2014). While effective, these methods may have limited generalization and might require complex manipulators. Motivated by these challenges, we explored one of the first applications of end-to-end deep learning for fabric manipulation with robot bed-making (Seita et al., 2019a), where we used supervised learning on high dimensional depth images to train a policy to grasp at a blanket corner. In subsequent work, we addressed two limitations of the bed-making setup: (1) the need for physical data collection, and (2) only learning the pick point, since we predefined the placing point. In Seita et al. (2020), we developed a fabric simulator to generate data in simulation, used Dataset Aggregation (Ross et al., 2011) to train a corner-pulling policy for smoothing fabrics from highly wrinkled configurations in a model-free manner, and then transferred it to a physical robot via domain randomization (Tobin et al., 2017). While this approach showed promising results, the policy is limited to smoothing and requires an algorithmic supervisor for other tasks. To address this, we subsequently proposed a model-based method, *VisuoSpatial Foresight (VSF)* (Hoque et al., 2020). This technique is based on Visual Foresight (Ebert et al., 2018) in that we use a large dataset of random environment interactions to learn a dynamics model, which we can then use for planning. Our contributions were to add depth sensing, and to demonstrate high-precision, multi-step smoothing and folding under a single policy. We have also explored approaches for fabric smoothing and folding by using correspondence, where given a demonstration applied on one fabric, we can "translate" it to another fabric (Ganapathi et al., 2021).

Architectures for Rearrangement of Deformables. Rearrangement (Batra et al., 2020) is a common task in robotics, and a recent paper proposes the Transporter Network (Zeng et al., 2020) architecture, which is well-suited for object rearrangement. Transporter Networks perform a brute-force deep feature matching search via a convolution to decide on pick-and-place actions. In a direct follow-up work, we proposed to extend the Transporter Network by allowing it to take in a separate goal image (as in the VSF work) to specify a desired target rearrangement (Seita et al., 2021). Second, we merged this to deformable object manipulation by developing a suite of simulated PyBullet (Coumans and Bai, 2020) tasks with cables, fabrics, and bags. To our knowledge, there is very little literature on manipulation of bags due to the complexities involved. With Transporter Networks, we demonstrated the first result of a (simulated) robot being able to open a bag, to insert item(s) in it, then to pick and place that bag inside a target zone.

Improving Precision and Speed of Surgical Robots. Cable-driven surgical robots such as Intuitive Surgical's da Vinci (Kazanzides et al., 2014) have errors and imprecision in their motion, which is problematic for automating surgical subtasks, as errors of even a few millimeters could result in cuts of human tissue. In one line of work, we demonstrated how to use two stages of supervised learning to better calibrate a da Vinci robot for faster and accurate debridement (Seita et al., 2018). We have similarly explored learning-based approaches to attain the best published results for surgical peg transfer (Hwang et al., 2020b), outperforming both a human surgeon and prior work using non-learning, open-loop methods (Hwang et al., 2020a). Tying this back to highly deformable object manipulation, we are currently extending this approach to improve existing automated surgical suturing results (Sen et al., 2016).

3 Ongoing and Future Directions

I have learned how, when, and why simulators such as PyBullet are useful for robotics researchers. While simulators never attain perfect real-world accuracy, I believe they are a useful tool because they enable algorithmic supervisors with perfect information (as in our fabric smoothing work), and facilitate benchmarks (Lin et al., 2020) and reproducible research. I also better understand the tradeoffs between model-free versus model-based methods, and imitation versus reinforcement learning. Going forward, I hope to build upon my existing research repertoire to expand the frontiers of robot manipulation and sim-to-real transfer. I also aim to facilitate the development of machine learning more broadly.

Going Beyond Pick-and-Place. Almost all my prior work in robotic manipulation relies on pick-and-place actions. This action space is simple and widely applicable, but is limited in that the robot cannot easily recover from failures if its initial pick point or the pulling motion is suboptimal (e.g., if it pulls a bag upwards and an item drops). I am interested in developing higher-rate control policies to react and address failures in real-time. Such approaches might involve merging different sensing modalities (Lee et al., 2019). I am also interested in challenging manipulation tasks that require moving away from pick-and-place entirely, such as with dynamic tossing (Zeng et al., 2019) or fabric draping. In recent work, we demonstrated how a parabolic action trajectory can enable a robot to perform vaulting, knocking, and weaving of fixed-endpoint cables (Zhang et al., 2021). I am currently strengthening the generalization capabilities of these robots and am applying dynamic manipulation for free-end cables.

Improving Imitation and Reinforcement Learning Algorithms. Deep RL is a promising technique to train robots, but suffers from brittleness and sample inefficiency (Duan et al., 2016); addressing these challenges could enable more applications of RL for the robotic manipulation tasks I have explored. In recent and ongoing work, I have explored robust RL algorithms (Pan et al., 2019) and sought to reduce exploration requirements by combining demonstrations with RL (Seita et al., 2019b). I am currently extending the Deep Q-learning from Demonstrations algorithm (Hester et al., 2018) to the offline setting with multiple teachers by appropriately designing curricula of samples.

Expanding my Horizons. I have taken steps towards understanding research areas that might be useful for robotic manipulation, such as offline RL (Levine et al., 2020), curriculum learning (Bengio et al., 2009), and human-robot interaction (Goodrich and Schultz, 2007). We have taken first steps to incorporate these by leveraging a large offline dataset for VSF to train a dynamics model, by using a curriculum of teachers in RL, and by requesting human supervisors for help during interactive imitation learning in ongoing work (Hoque et al., 2021). In future work, I plan to further explore and develop these subfields.

Long-Term Vision. One of the things that excites and inspires me about robotics is the thought of *getting robots to manipulate arbitrary, unseen objects at the level of a skilled human and beyond*. By doing so, we open the doors towards getting robots deployed throughout the world for the betterment of society. Let's do it.

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