Robotic Dough Shaping
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Abstract: Robotic manipulation of deformable objects gains great attention due to its wide applications including medical surgery, home assistance, and automatic food preparation. The ability to deform soft objects remains a great challenge for robots due to difficulties in defining the problem mathematically. In this paper, we address the problem of shaping a piece of dough-like deformable material into a 2D target shape presented upfront. We use a 6 degree-of-freedom WidowX-250 Robot Arm equipped with a rolling pin and information collected from an RGB-D camera and a tactile sensor. We present and compare several control policies, including a dough shrinking action, in extensive experiments across three kinds of deformable materials and across three target dough shape sizes, achieving the intersection over union (IoU) of 0.90. Our results show that: i) rolling dough from the highest dough point is more efficient than from the 2D/3D dough centroid; ii) it might be better to stop the roll movement at the current dough boundary as opposed to the target shape outline; iii) the shrink action might be beneficial only if properly tuned with respect to the expand action; and iv) the Play-Doh material is easier to shape to a target shape as compared to Plasticine or Kinetic sand. Video demonstrations of our work are available at https://youtu.be/ZzLMxuTtd4

Keywords: Robotics and Mechatronics, Machine Vision and Perception, Sensors and Actuators

1. INTRODUCTION

Robotic manipulation of deformable objects has applications in various domains, including robotic surgery, home robotic solutions, and automated food preparation. A ubiquitous challenge throughout this area of research is that robotic interactions with deformable materials are highly complex, often nonlinear, and difficult to model, which further increases the difficulty of action selection and real-time computation. Another challenge is the gap between simulation and real world environments, especially amplified for deformable objects that are often impossible to model perfectly.

The particular task that this work focuses on is shaping elastoplastic solid 3D deformable objects to a predefined target 2D shape on the horizon axis. To make the problem tractable while keeping the solution generalizable, we design a simple action space to roll out a piece of dough against a horizontal flat surface and track the dough’s shape progression with a low-dimensional feature space. We apply and test our methods directly in real world, skipping the simulation phase to avoid the sim-to-real gap. For the hardware execution, we design an end-effector attachment to the robot arm. Our main contributions are:

• Efficient heuristic dough shaping methods with multi-modal (vision and 3D point clouds) information processing, and their evaluations on three kinds of materials with different energy density.
• Roll Dough GUI Application1 supporting various configurations and methods.
• Material properties analysis with a tactile sensor which can inform the robot control strategies in further work.

2. RELATED WORK

2.1 Deformable Object Manipulation

Compared to rigid bodies, the new challenges introduced by Deformable Object Manipulation (DOM) can be generally grouped by three aspects: i) designing new devices and algorithms for more accurate sensing and perception [1], [2], [3], [4], [5], ii) modeling the complex deformation [6], [7], [8], [9], and iii) the high degree of freedom in planning [10], [11], [12] and control [13], [14] of manipulation actions. When conducting experiments, the objects usually have a relatively simple shape: either linear such as ropes [4], [15] and cables [16], or planar objects such as cloth [17], [18] and gauze [19]. In this work, we focus on exploring i) and iii) for dough-like object, which is relatively less explored yet very common in real life.

2.2 Policy Learning

Many existing works use reinforcement learning (RL) to approach the task. PlasticineLab [20] establishes one of the first deformable object manipulation benchmarks and evaluates popular RL algorithms on them. The work [21] is perhaps the most similar to ours as it also deals with dough shaping with an end-effector, and it requires a random exploration period to learn the policy before solving the task. We research on heuristic policies, which turn out to be still very efficient. [18] proposes an RL algorithm that shares the same intuition as ours: dynamic manipulation with delta physics. Instead of deciding the next action based on the holistic view of current state, another perspective is to base it on how far the current state is from the target state, thus the “delta”. This is particularly useful for deformable objects where the generalization and state characterization are much harder than for regular rigid bodies.

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2 Available at https://github.com/jancio/Robotic-Dough-Shaping
2.3 Tactile Sensing

Besides the visual input, a robot is desired to have human-like tactile sensing abilities for contact-rich tasks. The ability to sense through physical contact is especially important when the vision information is not available (limited light source) or under large distortion (large reflection or underwater). The study of tactile sensing has started more than 30 years ago [22]. The tactile information is generally used in two ways: i) haptic data can be used independently for object identification [23], [24], [25], [26], or ii) the contact information can be combined with other inputs, such as the visual inputs, so that robots can learn from multi-modal representations [27], [28], [29]. Using multimodal fusion, tactile sensing was first integrated with other sensor inputs based on handcrafted features [28]. For example, the work [23] demonstrates the sensing of compliance, texture, and thermal properties, based on which Bayesian exploration was used for object identification. More often, tactile information was used with vision input. For instance, Lee et al. [29] used both vision and tactile information to train a self-supervised model for a peg insertion task.

3. METHODS

In this section, we present the hardware setup (Section 3.1), initial and target dough shape definition (Section 3.2), Roll Dough Algorithm including various control methods (Section 3.3), and approach to the tactile sensing of the dough (Section 3.4).

3.1 Hardware setup

As a robotic platform, we used a 6 degree-of-freedom WidowX-250 Robot Arm that we equipped with a rolling pin. For perception, we utilized the Intel RealSense D435i RGB-D camera mounted 60 cm above the robot workspace. The whole setup is shown in Figure 1 (left).

![Robot and camera setup: 6 degree-of-freedom WidowX-250 Robot Arm equipped with a steel rolling pin and Intel RealSense D435i RGB-D camera mounted 60 cm above the robot workspace.](image)

We considered the following three dough-like deformable materials: Play-Doh (green), Plasticine (orange), Kinetic sand (purple).

- Play-Doh – easiest to deform, dries out fastest.
- Plasticine – harder to deform, dries out slowly.
- Kinetic sand – easy to deform only if the deformation is slow, shares some properties of granular media, does not dry out.

3.2 Initial and Target Dough Shape

We standardized the initial dough shape using a plastic cylindrical mold with the diameter of 5.6 cm and height of 1.6 cm, placed at a fixed location with respect to the target shape (Figure 1 (left)). This configuration ensured same initial conditions for all our experiments. However, our methods can handle a general case when this is not satisfied.

We considered three circular 2D target shapes with diameters 3.5, 4.0, and 4.5 inch, denoted by $T_{3.5}$, $T_{4.0}$, and $T_{4.5}$ respectively. Each target shape was printed on a paper and placed just below the transparent workspace plate (Figure 1 (left)).

3.3 Roll Dough Algorithm

To roll the dough, we developed an iterative procedure presented in Algorithm 1 and implemented as a GUI application (see Appendix 7.1 for screenshots) supporting various configurations and methods available at https://github.com/jancio/Robotic-Dough-Shaping.

At the beginning, we detect a circular 2D target shape in an RGB image using the OpenCV library [30] (line 2). In an iterative manner, we then similarly detect contours of the current dough shape (lines 3 and 8), evaluate the intersection over union (IoU) metric between the current dough projected 2D shape and the target 2D shape (lines 4 and 9), and calculate the next roll start point $S$ and end point $E$ (lines 5 and 10). Given these 3D points, the robot arm with the rolling pin touches the dough at point $S$ and performs the roll action to point $E$ (line 7). The algorithm terminates when either the maximum time limit $T_{max}$ or the minimum IoU $IoU_{min}$ is reached (line 6).

Algorithm 1: Roll Dough Algorithm

1. $t \leftarrow 0$;
2. $targetShp \leftarrow captureTargetShape();$
3. $currentShp \leftarrow captureCurrentShape();$
4. $IoU \leftarrow evaluate(currentShp, targetShp);$
5. $S, E \leftarrow plan(currentShp, targetShp);$
6. while $t < T_{max}$ and $IoU < IoU_{min}$ do
7. \hspace{1em} roll($S, E$);
8. \hspace{1em} $currentShp \leftarrow captureCurrentShape();$
9. \hspace{1em} $IoU \leftarrow evaluate(currentShp, targetShp);$
10. \hspace{1em} $S, E \leftarrow plan(currentShp, targetShp);$

In the following subsections, we provide details on the roll start point calculation method (Section 3.3.1), roll end point calculation method (Section 3.3.2), and an extension with a shrink action (Section 3.3.3).

3.3.1 Roll Start Point Method

We choose the roll start point $S$ as a point from where the dough should be distributed to other areas where it is currently missing. As such, we consider the following four roll start point methods.
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- **Centroid-2D** – We calculate the x and y coordinates $(S_x, S_y)$ of the start point $S$ as a 2D geometric center of the current dough shape. Using K-Nearest Neighbors we then find three closest points (by their x and y coordinates) in the 3D point cloud of the current dough shape and set the z coordinate $S_z$ to be the average z coordinate of these points.

- **Centroid-3D** – Utilizing the whole dough point cloud data, we calculate the start point $S$ as a 3D location of the center of mass of the dough (assuming constant material density).

- **Highest-Point** – We set the start point $S$ to be the highest point in the dough point cloud.

- **Differential-Inverses-Renderings** – One intuitive approach is to differentiate a loss based on distribution difference between current point cloud and target shape. Before the iteration starts, we discretize the target shape as 3D point clouds, then back propagate the density aware chamfer loss \[ L_{DCD} = \frac{1}{2} \left( \frac{1}{|S_1|} \sum_{x \in S_1} \left( 1 - \frac{1}{n_x} e^{-\alpha ||x-y||} \right) \right) \] \[ + \frac{1}{|S_2|} \sum_{y \in S_2} \left( 1 - \frac{1}{n_y} e^{-\alpha ||y-z||} \right) \] with $\alpha = 1000$, between the target point distribution $S_1$ and current point cloud distribution $S_2$ to get point wise gradient. There are several ways to plan the movement direction from this gradient: using the mean value of the gradient or using the gradient with the maximum magnitude. We choose to use the gradient with largest magnitude because the mean gradient could have 0 magnitude in the xy plane if the point cloud is perfectly aligned in the center.

3.3.2 Roll End Point Method

We roll the dough from the start point $S$ in the direction $\vec{d}$ in which there is a largest gap between the current and target shape, i.e., we employ the “minimize the largest error first” heuristic. We ignore candidate directions where the dough is outside of the target shape. To set the roll end point $E$ in this direction, we consider the following two variants, also illustrated in Figure 2 (a).

- **Target** – We set the x and y coordinates $(E_x, E_y)$ of the roll end point $E$ to be a 2D intersection point of the vector $\vec{d}$ and the target shape outline.

- **Current** – We set $(E_x, E_y)$ to be a 2D intersection point of the vector $\vec{d}$ and the current dough outline. In both methods, the z coordinate $E_z$ is $S_z$.

3.3.3 Shrink Action

In theory, the roll end point methods should not spread the dough outside of the target shape. However, the dough can be moved there accidentally due to any sort of inaccuracies and the above-proposed Roll Dough Algorithm does not explicitly rectify the dough shape in such cases to increase IoU. We thus also consider a variant of the Roll Dough Algorithm which allows a shrink action to correct the dough shape and achieve higher IoU in such cases. At each iteration of the Roll Dough Algorithm, if any point on the current dough shape contour is found to be outside of the target shape, we execute the shrink action instead of the roll action. We set the start point of the shrink action to be the furthest point on the current dough shape contour outside of the target shape in the direction towards the target shape center, and the end point to be the point on the target shape outline in this direction. The z coordinate of both start and end points is set to touch the workspace plate.

We consider the following two variants of the shrink action, also illustrated in Figure 2 (b-c).

- **Forward-Shrink** – The dough is pushed by a rolling pin in its usual roll orientation.

- **Side-Shrink** – The dough is pushed by the side of the rolling pin. This can also simulate a use of another tool, such as spatula, to perform the shrink action.

We further denote the original variant without the shrink action as **Shrink-Disabled**.

3.4 Dough Tactile Sensing

Tactile sensors are capable of detecting a rich range of information including stiffness, compliance and thermal properties. In this paper, we implemented a resistance based strain gauge, which is programmed to give feedback on the stiffness of the three types of dough. This information can be used to determine the planning of force amplitude, rolling speed and rolling iteration numbers.

We used an off-the-shelf force sensitive sensor to detect the stiffness of the contacting material (Model Number: SEN-09375 ROHS). Figure 3 (a) shows the device on the left and the structure of the device on the right. The force sensor consists of three layers: a semi-conductive layer, a space, and a substrate with two interdigitating electrodes not overlapping. The device has an infinitely high output impedance if no force is applied. When a pressure is applied, the first layer and the third layer are partially contacted, causing the impedance of the device to change. The FSR device is connected with a reference resistor in series (Figure 3 (b)). The output voltage from
the circuit is
\[ V_{\text{out}} = \frac{R_{\text{ref}}}{R_{\text{ref}} + R_{\text{FSR}}} V_{\text{CC}} \]

An Arduino UNO was used to control and gather data from the tactile sensor.

Fig. 3. (a) Force sensitive resistor (FSR): an off-the-shelf device (left) and the working principle of an FSR (right). (b) Circuit used for tactile sensing consisting of an FSR sensor, a resistor, and an Arduino UNO.

Compliance is defined as the ratio of a deflection of the object over the applied force. In our implementation, we mount the tactile sensor on the rolling pin held in the robot gripper and program the robot to press against the contacting material and move a constant distance \( \Delta x \) vertically while recording the reacting force \( \Delta F \) generated during this process. For simplification, we always apply the force perpendicular to the contacting surface as the angle of the applied force also affects the detected compliance.

4. EXPERIMENTS

We evaluated the roll start point methods (Centroid-2D, Centroid-3D, Highest-Point), roll end point methods (Target, Current), and shrink action variants (Shrink-Disabled, Forward-Shrink, Side-Shrink), in the following experiments across three target shapes \((T_{3.5}, T_{4.0}, T_{4.5})\) and three materials \((\text{Play-Doh, Plasticine, Kinetic sand})\).

A) Performance across materials (Section 4.1)
B) Roll start point methods (Section 4.2)
C) Roll end point methods (Section 4.3)
D) Shrink action (Section 4.4)
E) Performance across target shapes (Section 4.5)
F) Differentiable rendering (Section 4.6)
G) Tactile sensing (Section 4.7)

We ran each experiment \((A-E)\) \(N = 3\) times and set the maximum time limit \(T_{\text{max}} = 5\) min for each run. As evaluation metrics, we used: i) the intersection over union (IoU) between the current dough projected 2D shape and the target 2D shape, and ii) the maximum dough height obtained from the dough point cloud.

Video demonstrations of our experiments are available at https://youtu.be/ZzLMxuITdt4

4.1 Performance Across Materials

We investigated the differences between three dough-like deformable materials across three roll start point methods. We set the target shape to the middle size \(T_{4.0}\), roll end point method to Target, and disabled the shrink action.

The results in terms of IoU over time are shown in Figure 4. We can observe that the runs with Play-Doh tend to achieve the highest IoU for any start point method which suggests it is the easiest to expand to match the target shape. Plasticine seems to be slightly more difficult to roll than Play-Doh. The runs with Kinetic sand were very unstable and we stopped the experiment if the material separated into several disconnected parts.

Figure 5 further shows the results in terms of the maximum dough height over time. We can see that the runs with Play-Doh tend to achieve lower maximum dough heights which, similarly to the IoU metric, suggests it is the easiest to deform to match the target shape.

Overall, these observations reflect the material properties described in Section 3.1. In further experiments we thus focused primarily on Play-Doh as it was the best material to demonstrate the dough shaping.

4.2 Roll Start Point Methods

We compared the performance of the three roll start point methods on Play-Doh as well as Plasticine. As shown in Section 4.1, the runs with Kinetic sand were very short and unstable so we did not consider it further. We set the target shape to the middle size \(T_{4.0}\), roll end point method to Target, and disabled the shrink action.

As can be seen from Figure 6, the Centroid-2D method performed the worst in terms of IoU suggesting that the depth information that the Centroid-3D and Highest-Point methods utilize is important in determining the point from where to distribute the dough. The Highest-Point method seems to be the best out of the three. We hypothesize this can be explained by the observations that the Centroid-3D method was susceptible to converging to similar movements while the Highest-Point method had higher variation in the start point location as the highest dough point was changing frequently. In the following experiments we thus used the Highest-Point method.

4.3 Roll End Point Methods

We further compared the performance of the Target and Current roll end point methods. We set the target shape to the largest size \(T_{4.5}\) where the gap between the current and target dough shape is largest and so the differences between the Target and Current roll end point methods are most visible. We used the Play-Doh material, the Highest-Point roll start point method, and disabled the shrink action.

Our initial hypothesis that rolling beyond the dough boundary (determined at roll start) should expand the dough more towards the target shape as the dough boundary moves in that direction during the roll. Together with our preliminary experiments this suggested that the Target method should achieve higher IoU faster which also informed the design of other experiments and the use of the Target method. However, as shown in Figure 7 (left), the Current method achieves higher IoU, especially later during the run. One interpretation could be that the Current method does more and shorter iterations in a given time, however, that was not the case as the total numbers of iterations of the Roll Dough Algorithm were very similar. Therefore, we think a viable explanation could
Fig. 4. Intersection over union over time in terms of dough-like deformable materials (Play-Doh, Plasticine, Kinetic sand) for roll start point methods: Centroid-2D (left), Centroid-3D (middle), Highest-Point (right). Three runs per condition.

Fig. 5. Maximum dough height in terms of dough-like deformable materials (Play-Doh, Plasticine, Kinetic sand) for each roll start point method: Centroid-2D (left), Centroid-3D (middle), Highest-Point (right). Three runs per condition.

Fig. 6. Intersection over union over time in terms of roll start point method (Centroid-2D, Centroid-3D, Highest-Point) for dough-like deformable materials Play-Doh (left) and Plasticine (right). Three runs per condition.

be that this is caused by the differences in the dynamics of the shorter vs. longer roll movements. Indeed, humans would probably also stop the roll at (or close to) the dough boundary or at the instantaneous moving dough boundary, rather than rolling all the way to the target shape and rolling on a table where there is no dough. It would be thus interesting to further experiment with a method that ends the roll at the instantaneous moving dough boundary which would require a camera mounted on the end-effector.

4.4 Shrink Action

We investigated the influence of enabling the shrink action and evaluated the performance in terms of IoU in three settings: Shrink-Disabled, Forward-Shrink, and Side-Shrink. To make valid comparisons, when the shrink action was enabled we considered only the runs where the shrink action was eventually used. We also set a threshold (in terms of the width of the target outline) to prevent triggering the shrink action in case of small dough expansions beyond the target shape outline. We set the target shape to the smallest size $T_{3.5}$ when it is easiest to expand or move the dough outside of the target shape and so the differences between the shrink settings are most visible. We used the Play-Doh material, the Highest-Point roll start point method, and the Target end point method.

Figure 7 (middle) shows that the Shrink-Disabled setting achieves higher IoU than either of the settings with shrink action enabled. As can be seen from the four worst runs with shrink action enabled, once the shrink action was performed the IoU plateaued afterwards. This suggests that there is a tradeoff between dough expansion and shrinking and needs to be tuned. For instance, the shrink action should be allowed only if the estimated gains in IoU from its execution are higher than those from the expand action. Also, it might be better to enable the shrink action towards the end of the run, for example, once a certain minimum IoU is achieved.

Comparing Forward-Shrink and Side-Shrink, the Forward-Shrink setting performed much worse once the shrink action was executed. Indeed, pushing the dough with the rolling side is not very efficient as it likely results in a roll over the dough. The Side-Shrink provides a much more rigid push.

4.5 Performance Across Target Shapes

We also examined the impact of the target shape size on performance. To make valid comparisons between different target size shapes, we evaluated the increase in IoU with respect to the initial IoU. We used the Play-Doh material, the Highest-Point roll start point method, the Target end point method, and disabled the shrink action.

As shown in Figure 7 (right), for smaller target shapes the increase in IoU can be achieved faster. Since we used the Target end point method this might just reflect the observations from Section 4.3 as rolling only to the current shape boundary is more similar to rolling to the target shape outline for smaller target shapes than for larger target shapes. It would be thus interesting to further repeat this experiment with the Current end point method. In this experiment, we also recorded the highest IOU exceeding 0.90.
4.6 Differentiable Rendering

We tested the differentiable method by simulating synthetic deformation of the dough point cloud to the target shape, and ran real robot experiments towards the target shape $T_{4,5}$ for each material. The change of Chamfer loss after across iterations is shown in Figure 8. With these preliminary results we demonstrate the use of differentiable rendering for dough shaping task and further experiments are needed to fully evaluate this approach.

4.7 Tactile Sensing

We used tactile sensing to detect the stiffness of the three materials introduced above. The information obtained here can be used in future to determine the force applied when rolling different materials. Figure 9 (a) shows the experimental setup for tactile sensing. We programmed the robot to push the dough a fixed vertical distance and recorded 5 measurements for each material. Before each measurement we reshaped the dough into the initial shape using a mold. As shown in Figure 9 (b), the resisting forces differ considerably across materials (smaller force implies softer material). This suggests the material stiffness measurements can help the dough shaping control policy adapt to different materials.

5. CONCLUSION

In this paper, we addressed the problem of shaping a piece of dough-like deformable material into a predefined 2D target shape. We used a 6 degree-of-freedom WidowX-250 Robot Arm equipped with a rolling pin and information collected from an RGB-D camera and a tactile sensor.

We developed a Roll Dough GUI Application and proposed several control policies, including a dough shrinking action. We evaluated these policies in extensive experiments across three kinds of deformable materials and across three target dough shapes, exceeding the intersection over union (IoU) of 0.90.

Our results show that: i) rolling dough from the highest dough point is more efficient than from the 2D/3D dough centroid; ii) it might be better to stop the roll movement at the current dough boundary as opposed to the target shape outline; iii) the shrink action might be beneficial only if properly tuned with respect to the expand action; and iv) the Play-Doh material is easier to shape to a target shape as compared to Plasticine or Kinetic sand.

Video demonstrations of our work are available at https://youtu.be/ZzLMxulTdt4

6. FUTURE WORK

The following ideas can be investigated as future work.

**Evaluation Metrics.** Instead of the IoU metric evaluating the projection of the current dough shape, employ a 3D evaluation metric, for example, to explicitly optimize for even dough height distribution.

**Target Shapes.** Evaluate generalizability of our method to different kinds of target shapes such as ellipses.

**Materials.** Choose a set of dough-like deformable materials with intentionally different quantitative physical properties to demonstrate generalizability of our method to different materials. Also, as we observed, Play-Doh hardens over time and becomes difficult to spread/roll. It might be thus useful to account for such changes in material properties over time and develop algorithms that adjust to time-evolving materials.

Fig. 7. Intersection over union over time in terms of: roll end point method (left), shrink action setting (middle). Increase in intersection over union over time in terms of target shape size (circle diameters in inch) (right). Three runs per condition.

Fig. 8. Top: Deforming the source shape to target shape using SGD optimizer with differentiable point-cloud rendering. Bottom: Real robot experiment with Play-Doh, Plasticine, Kinetic sand, showing the Chamfer distance between current and target dough shape at each iteration.

Fig. 9. (a) Experimental setup for tactile sensing: tactile sensor glued on the rolling pin (left), robot gripper controlled to apply force perpendicular to the dough surface (right). (b) Resisting forces of the three deformable materials.

6. FUTURE WORK
Policy Learning and Tactile Sensing. Learn the dough rolling policy online and/or from demonstrations. Incorporate stiffness measurements from dough tactile sensing as a prior for learning. Also, the tactile sensor can be attached just above the rolling pin so that it can get in contact with the pin but does not prevent rolling. The stiffness measurements can be then used during the roll action, for example, to adjust the rolling pin height, and to determine the moment the dough was touched.

Roll Start and End Point Methods. Experiment with adding little random noise to the selection of the roll start point, based on observations in Section 4.2. Experiment with a new roll end point method that ends the roll within a certain tolerance of the instantaneous moving dough boundary which would require a camera mounted on the end-effector, as suggested in Section 4.3.

See 7.2 for further future work suggestions.

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7. APPENDIX

7.1 Roll Dough GUI Application

Fig. 10. Screenshot of Roll Dough GUI Application available at https://github.com/jancio/Robotic-Dough-Shaping

7.2 Further Future Work Suggestions

Shrink Action. Examine the tradeoff between the expand and shrink action, as suggested in Section 4.4, for instance, the shrink action can be allowed only if the estimated gains in IoU from its execution exceed those from the expand action. Also, evaluate a more realistic scenario when two tools are used: one for the expand action and the other for the shrink action.

Physical Model. Currently in our work, we are not using any physical model of the plastic deformation. One exciting future direction is to apply a physical model and differentiate it to get the derivatives to aid the planning. However, since we have access to the dough point cloud, we can apply physically based differentiable “rendering” to get the gradient which aids in planing of the roll. Our current work does not consider the appearance of the material which could incorporate the surface normal information and the material reflectance (for example, color information). It is also interesting to apply differentiable surface splatting to compute the gradient. Besides the differentiable visual perceptions, we could also differentiate the physical process with simulator, which can better predict object deformation after applying force.

Robotic Platforms. Demonstrate generalizability of our method to various robotic platforms, for example, with the Kinova Gen3 robotic arm.