RoboCook: Long-Horizon Elasto-Plastic Object Manipulation with Diverse Tools

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Abstract: Humans excel in complex long-horizon soft body manipulation tasks via flexible tool use: bread baking requires a knife to slice the dough and a rolling pin to flatten it. Often regarded as a hallmark of human cognition, tool use in autonomous robots remains limited due to challenges in understanding tool-object interactions. Here we develop an intelligent robotic system, RoboCook, which perceives, models, and manipulates elasto-plastic objects with various tools. RoboCook uses point cloud scene representations, models tool-object interactions with Graph Neural Networks (GNNs), and combines tool classification with self-supervised policy learning to devise manipulation plans. We demonstrate that from just 20 minutes of real-world interaction data per tool, a general-purpose robot arm can learn complex long-horizon soft object manipulation tasks, such as making dumplings and alphabet letter cookies. Extensive evaluations show that RoboCook substantially outperforms state-of-the-art approaches, exhibits robustness against severe external disturbances, and demonstrates adaptability to different materials.

Keywords: Deformable Object Manipulation, Long-horizon Planning, Model Learning, Tool Usage

1 Introduction

Think about all the steps and tools a robot would need to use in order to make a dumpling from a lump of dough. This scenario contains three fundamental research problems in robotics: deformable object manipulation [1, 2, 3, 4], long-horizon planning [5, 6, 7, 8], and tool usage [9, 10, 11, 12]. The task poses significant challenges to the robot, because it involves decisions at both discrete (e.g., which tool to use) and continuous levels (e.g., motion planning conditioned on the selected tool).

To address these challenges, we propose RoboCook, a framework that perceives, models, and manipulates elasto-plastic objects for long-horizon tasks like making dumplings and alphabet letter cookies. RoboCook introduces three technical innovations. First, we apply a data-driven approach with a Graph Neural Network (GNN) [13, 14, 15] to learn highly complex interactions between the soft object and various tools purely from visual observations. Second, we combine a PointNet-based [16, 17] tool classification module with learned dynamics models to determine the most appropriate tool to use at the current task stage. Third, we use a self-supervised policy trained with synthetic data generated by our learned dynamics model to improve both performance and speed.

We carry out comprehensive evaluations to show RoboCook's effectiveness, robustness, and generalizability. Figure 1 shows a typical successful trial of making a dumpling. To showcase robustness, we apply external perturbations during real-time execution, and RoboCook still succeeds in making a dumpling. To demonstrate generalizability, we test RoboCook to make alphabet letter cookies and RoboCook outperforms four strong baselines by a significant margin. RoboCook can also generalize to various materials by making a particular shape on different materials without retraining.

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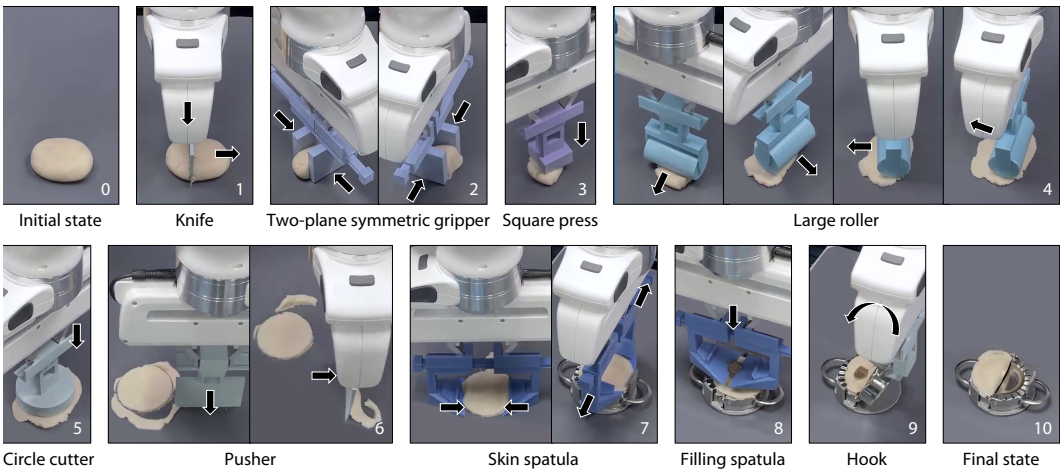

Figure 1: **Making dumplings.** RoboCook makes a dumpling from a piece of dough in nine steps: The robot (1) cuts the dough to an appropriate volume, (2) pinches the dough and regularizes the shape, (3) presses to flatten the dough, (4) rolls to flatten the dough further, (5) cuts a circular dumpling skin, (6) removes the excess dough, (7) picks and places the skin onto the mold, (8) adds the filling, and (9) closes and opens the mold. The black arrows denote the moving direction.

2 Related Work

Long-horizon deformable object manipulation. Real-world deformable object manipulation is a challenging task [18, 19, 20]. The innate high DoFs, partial observability, and non-linear local interactions make deformable objects hard to represent, model, and manipulate [21, 22, 23]. Conventional approaches in deformable object manipulation choose model-based methods [24, 25, 26, 27] or adaptive methods [28, 29, 30], yielding complex system identification problems. For example, Li et al. [27] proposes a differentiable simulator as the surrogate of real-world elasto-plastic objects. However, these simulators are based on approximate modeling techniques, resulting in a noticeable sim-to-real gap that hinders their application to real-world scenarios . There have been efforts toward learning to manipulate from expert demonstrations [31, 32, 33]. This paradigm is used in manipulating liquid [11], sand [29], and dough [34]. Despite these successes, obtaining the demonstration is expensive and sometimes prohibitive. Another recent trend is to learn a dynamics model from high-dimensional sensory data directly for downstream manipulation tasks [18, 35, 36, 37, 15, 38]. While these approaches show impressive results, they only consider short-horizon tasks using just one tool. In contrast, long-horizon tasks like dumpling-making require a reactive planner to understand the long-term physical effect of different tools to make the most effective discrete (e.g., which tool to use) and continuous (e.g., the action parameters) action decisions.

Tool usage. Tool usage is widely studied in cognitive science and robotics research [39, 40]. To study the process of human evolution, many researchers endorse tool usage as a main benchmark to evaluate the intelligence of living primates with respect to that of extinct hominids [41, 42, 43]. To equip robots with the same capability of tool usage as humans, prior works focus on teaching the robot the representation and semantics of tools or objects that potentially function like tools for downstream policy learning [11, 12]. In this work, we train the robot to understand the physical interactions between different tools and deformable objects from self-exploratory trials.

3 Method

The RoboCook framework has three major components: perception, dynamics, and closed-loop control. We first use an effective sampling scheme and intuitive tool representations for particle-based scene representation. Second, we train Graph Neural Networks (GNNs) as the dynamics model from the processed video dataset to accurately predict dough states during manipulation. Last,

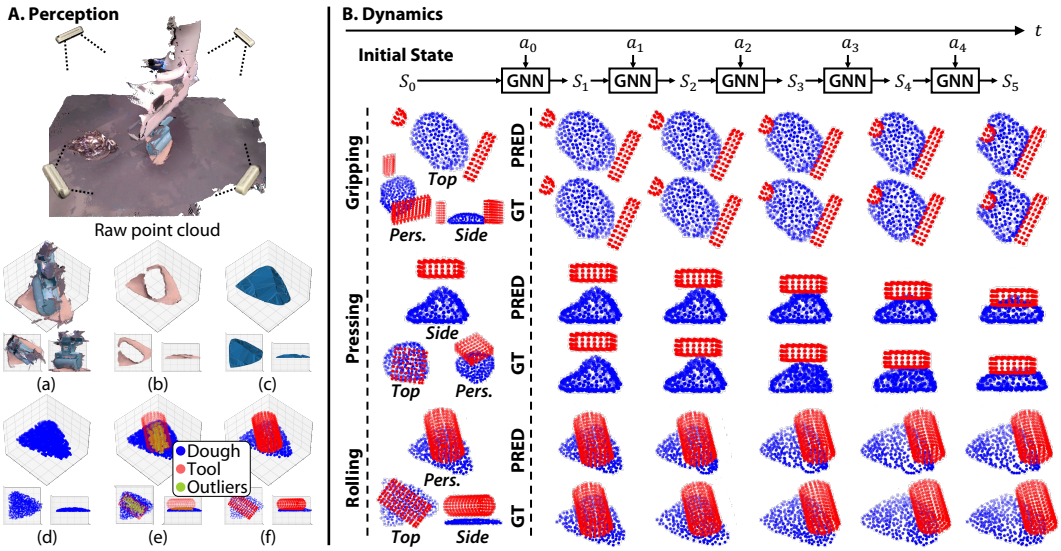

Figure 2: **Perception and dynamics of RoboCook**. **(A)** The input to the perception module is a point cloud of the robot's workspace captured by four RGB-D cameras. From the raw point cloud, we (a) crop the region of interest, (b) extract the dough point cloud, (c) reconstruct a watertight mesh (d) use the Signed Distance Function (SDF) to sample points inside the mesh, (e) remove points within the tools' SDF, and (f) sample 300 surface points. **(B)** We process videos of each tool manipulating the dough into a particle trajectory dataset to train our GNN-based dynamics model. The model can accurately predict long-horizon state changes of the dough in gripping, pressing, and rolling tasks. On the left are the initial states' perspective, top, and side views, and on the right is a comparison of model predictions and ground truth states.

a tool classifier selects the best tool for each substage in a long-horizon task and a self-supervised policy network performs closed-loop control.

3.1 Perception

The perception module aims to sample particles sparsely and uniformly for the downstream dynamics model. This task is challenging because of dough occlusions from the robot and tool and self-occlusions from the irregular and concave shape of the dough.

We merge point clouds from four calibrated RGB-D cameras and perform color segmentation to extract the dough point cloud. Then we apply either Poisson surface reconstruction [44] or alpha-shape surface reconstruction [45] to reconstruct a watertight surface of the dough, depending on occlusion levels. In heavy occlusion cases, alpha-shape surface reconstruction is usually worse at capturing concavities than Poisson surface reconstruction. However, we use it to secure a complete and singular mesh. With few or no occlusions, we combine Poisson surface reconstruction and the MeshFix algorithm [46] to generate a watertight mesh. We use the watertight mesh's Signed Distance Function (SDF) to sample points inside it randomly. To compensate for details lost during surface reconstruction, we apply a voxel-grid filter to reconstruct concavities by removing the points above the original dough point cloud. We also remove the noisy points penetrating the tool using the mesh's SDF. We compute the tool mesh's SDF from the robot's end-effector pose (recorded during data collection) and the ground-truth tool mesh. We then perform alpha-shape surface reconstruction and use Poisson disk sampling [47] to sample 300 points uniformly on the surface, capturing more details of the dough with a fixed particle number.

For different tools, we uniformly sample particles on the surface of their ground truth mesh to reflect their geometric features. The complete scene representation for the downstream dynamics model concatenates dough and tool particles. Section 6.1.1 and 6.1.2 of supplementary materials describe more data collection and preprocessing details.

3.2 Dynamics Model

Our GNN-based dynamics model predicts future states of dough based on the current state and actions of the tools with only 20 minutes of real-world data per tool. The rigid and non-rigid motions are each predicted by a multi-layer perceptron (MLP) and added together as the predicted motion by the GNN.

The graph of sampled particles at each time step is represented as $s_t = (\mathcal{O}_t, \mathcal{E}_t)$ with $\mathcal{O}_t$ as vertices, and $\mathcal{E}_t$ as edges. For each particle, $\mathbf{o}_{i,t} = \left(\mathbf{x}_{i,t}, \mathbf{c}^o_{i,t}\right)$, where $\mathbf{x}_{i,t}$ is the particle position i at time t, and $\mathbf{c}^o_{i,t}$ is the particle's attributes at time t, including the particle normal and group information (i.e., belongs to the dough or the tool). The edge between a pair of particles is denoted as $\boldsymbol{e}_k = (u_k, v_k)$, where $1 \leq u_k, v_k \leq |\mathcal{O}_t|$ are the receiver particle index and sender particle index respectively, and k is the edge index. Section 6.2.1 of supplementary materials provides more details on graph building.

Following the previous work [18], we use a weighted function of Chamfer Distance (CD) [48] and Earth Mover's Distance (EMD) [49] as the loss function to train the dynamics model:

$$\mathcal{L}(\mathcal{O}_t, \widehat{\mathcal{O}}_t) = w_1 \cdot \mathcal{L}_{\text{CD}}(\mathcal{O}_t, \widehat{\mathcal{O}}_t) + w_2 \cdot \mathcal{L}_{\text{EMD}}(\mathcal{O}_t, \widehat{\mathcal{O}}_t), \tag{1}$$

where $\mathcal{O}_t$ is the real observation, and $\widehat{\mathcal{O}}_t$ is the predicted state. We select $w_1 = 0.5$ and $w_2 = 0.5$ based on the experiment results. To be more specific, the CD between $\mathcal{O}_t, \widehat{\mathcal{O}}_t \subseteq \mathbb{R}^3$ is calculated by

$$\mathcal{L}_{\text{CD}}(\mathcal{O}_t, \widehat{\mathcal{O}}_t) = \sum_{\mathbf{x} \in \mathcal{O}_t} \min_{\mathbf{y} \in \widehat{\mathcal{O}}_t} \|\mathbf{x} - \mathbf{y}\|_2^2 + \sum_{\mathbf{y} \in \widehat{\mathcal{O}}_t} \min_{\mathbf{x} \in \mathcal{O}_t} \|\mathbf{x} - \mathbf{y}\|_2^2. \tag{2}$$

The EMD matches distributions of point clouds by finding a bijection $\mu : \mathcal{O}_t \to \widehat{\mathcal{O}}_t$ such that

$$\mathcal{L}_{\text{EMD}}(\mathcal{O}_t, \widehat{\mathcal{O}}_t) = \min_{\mu : \mathcal{O}_t \to \widehat{\mathcal{O}}_t} \sum_{\mathbf{x} \in \mathcal{O}_t} \|\mathbf{x} - \mu(\mathbf{x})\|_2. \tag{3}$$

We train the model to predict multiple time steps forward to regularize training and stabilize long-horizon future predictions. The training loss is calculated as a sum of distances between predictions and ground-truth states:

$$\mathcal{L}_{\text{train}} = \sum_{i=0}^{s} \mathcal{L}(\mathcal{O}_{t+i}, \widehat{\mathcal{O}}_{t+i}), \tag{4}$$

where the dynamics model takes $\widehat{\mathcal{O}}_{t+i-1}$ as the input to predict $\widehat{\mathcal{O}}_{t+i}$ when $i > 0$. By predicting a longer horizon during training, the model performs better when inferring much longer horizons. We select $s = 2$ based on experimental results. More implementation details on model training can be found in Section 6.2.2 of supplementary materials.

3.3 Closed-Loop Control

To solve long-horizon manipulation tasks involving multiple tools, the robot must determine (1) the best tool to use at each stage and (2) the optimal trajectory for the selected tool.

To answer the first question, we implement a tool classification module based on PointNet++ [17] that takes a concatenation of the input and output states of the dough as input and outputs probabilities of the 15 tools achieving the target state. We extract the features of the input and output point clouds separately with a PointNet++ classification layer. Then we feed the concatenated features to an MLP with a SoftMax activation layer to output probabilities.

The three tools with the highest probabilities are selected as candidates, and their optimal actions are planned. The robot selects the tool yielding the final state closest to the target and executes the planned actions. We let the module output three tool candidates instead of only one to increase our pipeline's error tolerance to the tool classifier.

To address the second question, we specify and parameterize the action space of the 15 tools based on human priors. Then we classify the tools into a few categories based on $|\mathcal{A}|$, the dimension of their

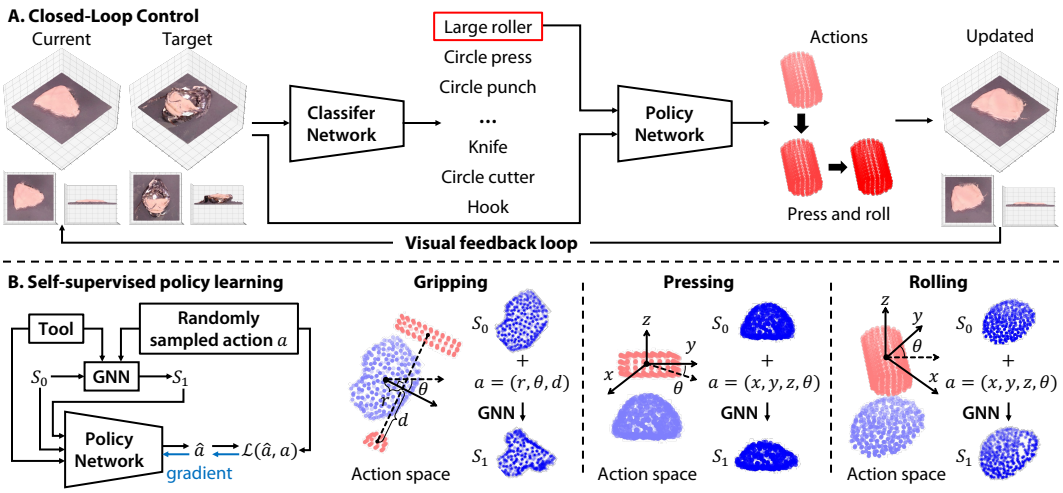

Figure 3: **Planning of RoboCook. (A)** PointNet-based classifier network identifies appropriate tools based on the current observation and the target dough configuration. The self-supervised policy network takes the tool class, the current observation, and the target dough configuration as inputs and outputs the manipulation actions. The framework closes the control loop with visual feedback. **(B)** We show the policy network architecture, the parametrized action spaces of gripping, pressing, and rolling, and how we generate the synthetic datasets to train the policy network.

action space. Section 6.3.1 of supplementary materials provides more details on the specification and justification of tool action spaces.

For grippers, rollers, presses, and punches, we collect data in the real world by random exploration in the bounded action space and learn their interaction model with the dough using a GNN. Then we generate a synthetic dataset with the dynamics model, train a self-supervised policy network to obtain the optimal policy, and execute closed-loop control with visual feedback. We use straightforward planners for other tools based on human priors. More implementation details can be found in Section 6.3.1 of supplementary materials.

To generate the synthetic dataset, we reuse the initial dough states acquired during data collection and randomly sample actions in the parameterized action space of each tool. As shown in Figure 3(A), the dough states before and after applying actions are the input, and the action parameters are the labels. We design a self-supervised policy network based on PointNet++. Given the continuous solution space of the action parameters, we formulate a multi-bin classification problem inspired by previous works on 3D bounding box estimation [50, 51]. First, we concatenate input and output point clouds, labeling them 0 or 1 for distinction. Next, we extract features using a PointNet++ layer. Finally, we feed the feature vector into separate classification and regression heads, both being MLPs with identical structures. The learned policy drastically improves the planning efficiency, and the complete pipeline only takes around 10 seconds of planning time to make a dumpling. More implementation details are described in Section 6.3.2 of supplementary materials.

During closed-loop control, cameras capture the workspace point cloud, which the perception module processes to obtain a clean and sparse point cloud of the dough. Our method takes the current observation and final target as input and returns the best tool and optimal actions, as shown in Figure 3(B). Then the robot picks up the selected tool, manipulates the dough, lifts its hand to avoid occluding the camera views, and plans the next move with visual feedback.

4 Experiments

In this study, we design and implement a hardware setup for soft body manipulation tasks, allowing easy selection and interchange of 15 tools, as shown in Figure 4. We demonstrate the RoboCook framework's effectiveness in long-horizon soft object manipulation tasks that require the use of mul-

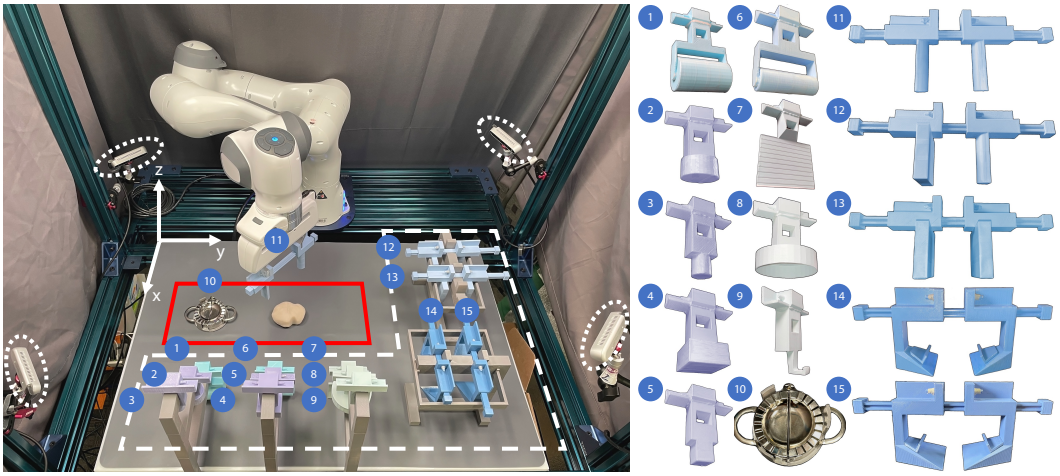

Figure 4: **RoboCook hardware and setup.** Left: Robot's tabletop workspace with xyz coordinates at top-left. Dashed white circles: four RGB-D cameras mounted at four corners of the table. Red square: dough location and manipulation area. Dashed white square: tool racks. Right: 15 tools: (1) large roller, (2) circle press, (3) circle punch, (4) square press, (5) square punch, (6) small roller, (7) knife/pusher, (8) circle cutter, (9) hook, (10) dumpling mold, (11) two-rod symmetric gripper, (12) asymmetric gripper, (13) two-plane symmetric gripper, (14) skin spatula, (15) filling spatula. Tools are 3D-printed, representing common dough manipulation tools. Section 6.4 of supplementary materials discusses the design principles of these 3D-printed tools.

tiple tools, such as making a dumpling from a randomly shaped dough and shaping alphabet letter cookies to compose the word 'RoboCook.' Additionally, RoboCook can complete these tasks under extensive human interference, including significant changes to the shape and volume, as shown in the second supplementary video, demonstrating its robustness to external perturbations.

4.1 Setup

We use the 7-DoF Franka Emika Panda robot arm and its parallel jaw gripper as the base robot. Four calibrated Intel RealSense D415 RGB-D cameras are fixed on vertical metal bars around the robot tabletop as shown in Figure 4. The cameras capture 1280×720 RGB-D images at 30 Hz. We also design a set of 3D-printed tools based on real-world dough manipulation tools. The tool designs and the tool-switching setup are described in Section 6.4 and 6.5 of supplementary materials.

4.2 Making Dumplings

The dumpling-making task is to manipulate a piece of dough and the given filling into a dumpling shape. The main challenge lies in choosing appropriate tools and planning effective action trajectories. We consider the task successful if the dumpling skin is thin enough and completely covers the filling. Dumpling-making is a highly challenging task—even a single error might break the entire pipeline. Our method reliably accomplishes the task as shown in Figure 1. We show a comparison with manipulation results of human subjects in Section 6.6 of supplementary materials.

RoboCook also demonstrates robustness against external perturbations during real-time execution. At each stage of dumpling making, a human disturbs the robot by deforming the dough, adding additional dough, or even replacing the dough with a completely different piece to deviate from the trajectory of the robot's original plan. For example, at the rolling stage, the human folds the flattened dough into a bulky shape. The robot decides to roll again to get a flatter dumpling skin. In a more challenging case, the human replaces the round dumpling skin with a completely different dough in a highly irregular shape. After this perturbation, the robot puts down the roller, picks up the knife to start again from the beginning, and successfully makes a dumpling. The complete process is shown in the second supplementary video. We also show a quantitative evaluation of the tool classification network in Section 6.7 of supplementary materials.

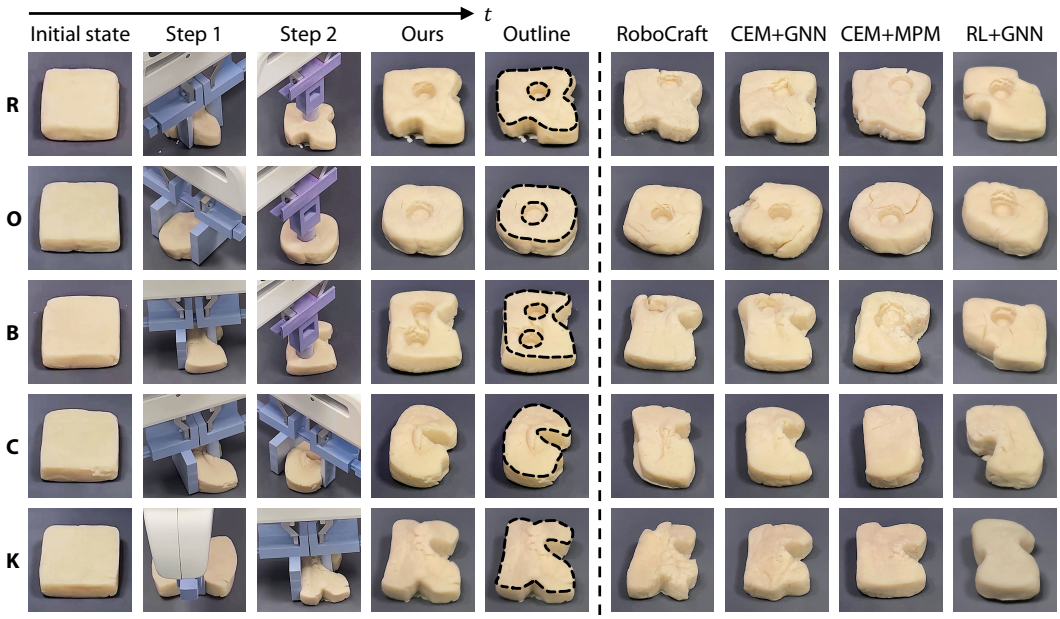

Figure 5: **Making alphabetical letter cookies.** We list R, O, B, C, and K shaping steps in Columns 1 to 4. Column 5 manually highlights the contour of the alphabetical letters. Columns 6 through 9 compare our self-supervised learned policy with three model-based planning baselines and one RL baseline. Our method can shape the dough closer to the target than all four baseline methods.

Methods	CD ↓	EMD ↓	CD of normal ↓	Human accuracy ↑	Planning time (s) ↓
Ours	**0.0062** $\pm$ **0.0007**	**0.0042** $\pm$ **0.0006**	**0.1933** $\pm$ **0.0345**	**0.90** $\pm$ **0.11**	**9.3** $\pm$ **1.5**
RoboCraft	0.0066 $\pm$ 0.0005	0.0044 $\pm$ 0.0006	0.2011 $\pm$ 0.0329	0.54 $\pm$ 0.43	613.7 $\pm$ 202.7
CEM+GNN	0.0066 $\pm$ 0.0007	0.0045 $\pm$ 0.0008	0.2043 $\pm$ 0.0431	0.52 $\pm$ 0.41	756.0 $\pm$ 234.5
CEM+MPM	0.0070 $\pm$ 0.0007	0.0046 $\pm$ 0.0006	0.1965 $\pm$ 0.0265	0.48 $\pm$ 0.35	1486.7 $\pm$ 512.8
RL+GNN	0.0077 $\pm$ 0.0007	0.0064 $\pm$ 0.0009	0.2041 $\pm$ 0.0414	0.17 $\pm$ 0.09	1867.9 $\pm$ 190.3

Table 1: **Quantitative evaluations.** We use CD and EMD between the point clouds and the CD between the surface normals to evaluate the results. We further profile how long these methods take to plan actions. Our method outperforms all baseline methods in these metrics by a large margin.

4.3 Making Alphabet Letter Cookies

The RoboCook framework demonstrates effectiveness and robustness in highly complicated manipulation tasks such as dumpling-making. This section explores its generalization ability in tasks requiring precise actions such as shaping alphabet letter cookies [18] without additional training.

Figure 5 shows that the RoboCook framework can accurately shape letters R, O, B, C, and K to compose the word 'RoboCook.' For R, the robot uses the two-rod symmetric gripper for cavities and the circle punch for the hole. For O, the tool classifier selects a two-plane symmetric gripper to pinch the square into a circle and the circle punch for the hole. Our method identifies the asymmetric gripper as suitable for B and locates accurate positions for the circle punch to press twice. Shaping C is more challenging due to the large distance between the initial and target shapes, but our method successfully plans gripping positions using closed-loop visual feedback. The robot combines the two-rod symmetric and asymmetric gripper for K to create cavities.

We compare our method with four strong baselines: (1) limited-memory BFGS [52] with GNN-based dynamics model (RoboCraft) [18]; (2) cross-entropy method (CEM) [53] with GNN-based dynamics model; (3) CEM with a Material Point Method (MPM) simulator [54]; and (4) Reinforcement Learning with GNN-based dynamics model. Qualitative results are shown in Figure 5.

Table 1 evaluates the results using Chamfer Distance (CD) [48], Earth Mover's Distance (EMD) [49] and CD between top surface normals. However, we recognize a discrepancy between how these met-

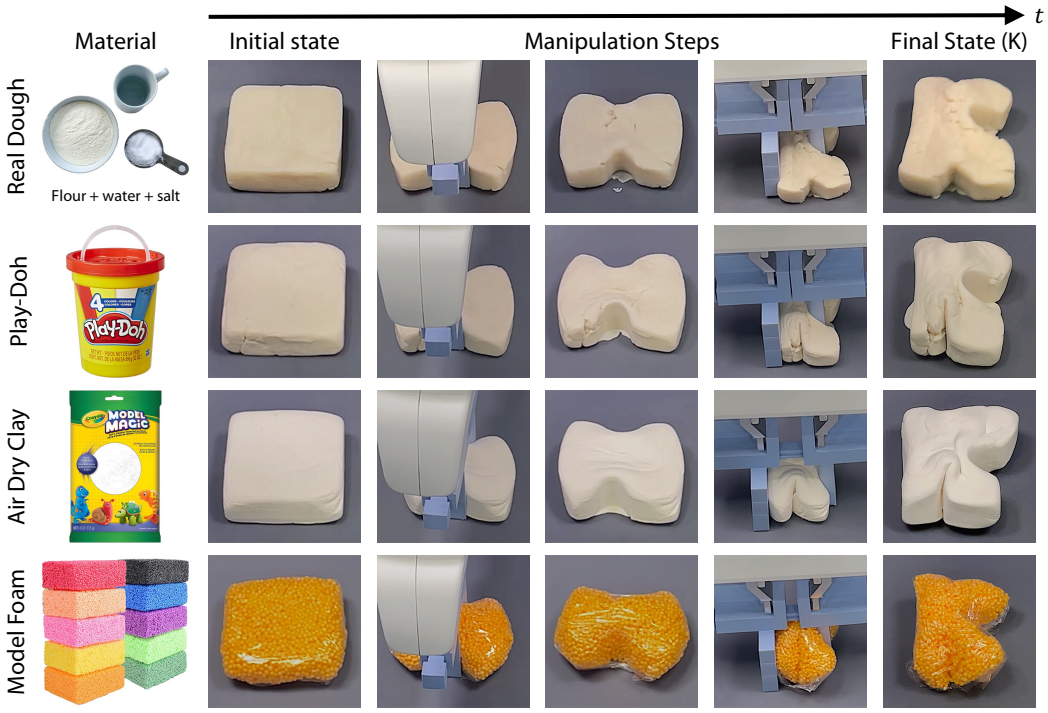

Figure 6: **Generalizing to different materials**. We showcase the dynamics model's capability to generalize to various materials by shaping a K without retraining.

rics measure the results and how humans perceive them - these metrics are prone to local noises while humans are good at capturing the holistic features of the dough. Therefore, we show the prediction accuracy of 100 human subjects on recognizing the letters for these five methods in Table 1. Another highlight of our method is its speed. Since the policy network only needs one forward prediction to output the actions for each tool, it is significantly faster than other methods that rely on forwarding the dynamics models many times. Section 6.8 and 6.9 of supplementary materials discuss more details about the human study and the RL baseline implementation.

We show that the dynamics model can generalize to various materials by shaping a K without retraining in Figure 6. We test on Play-Doh, Air Dry Clay, and Model Foam, each displaying notably different dynamics compared to our original dough made of flour, water, and salt. The dynamics model is trained solely on interaction data with the real dough.

5 Conclusion and Limitations

RoboCook demonstrates its effectiveness, robustness, and generalizability in elasto-plastic object manipulation with a general-purpose robotic arm and everyday tools. The main contributions of RoboCook include (1) tool-aware GNNs to model long-horizon soft body dynamics accurately and efficiently, (2) a tool selection module combined with dynamics models to learn tool functions through self-exploratory trials, and (3) a self-supervised policy learning framework to improve the performance and speed significantly. RoboCook pioneers solutions for tool usage and long-horizon elasto-plastic object manipulation in the efforts of building a generic cooking robot.

One limitation of RoboCook is the occasional failure of dough sticking to the tool. A solution is to design an automatic error correction system. We also recognize that RoboCook relies on human priors of tool action spaces to simplify planning. But these simplifications do not constrain generalization as they can be easily specified for new tools. Section 6.3.1 provides more justifications for this. Another limitation is that the subgoals are defined by humans. Higher-level temporal abstraction and task-level planning are required to get rid of them. Finally, RoboCook requires additional topology estimation to apply to cables and cloths [55], which is beyond the focus of this work.

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