Plasticine Manipulation Simulation with Optical Tactile Sensing

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***Abstract*—Deformable object manipulation is a difficult task for robots, and plasticine is one of the most challenging objects owing to its varying deformation properties. Previous works propose plasticine manipulation strategies by Reinforcement Learning (RL) in simulation, however, the observations used in these works cannot be transferred into reality. In this work, we introduce optical tactile sensors into plasticine manipulation simulation as end effectors to produce transferable observations. Such sensors can provide tactile images as the observations which are available in both simulation and reality. The simulator *Tacchi* is leveraged for RL environment setup, with the von Mises yield criterion used in elastoplastic object modelling. The experiments show the observations and rewards in the proposed simulation environment that can be used benchmark the plasticine manipulation task.**

I. Introduction

Robot manipulation is a popular research topic, and deformable object manipulation is a sophisticated problem in this area. Due to the softness and complex deformation properties, such objects are hard to model. However, deformable objects widely exist in medical, industrial, and home environments. In this kind of object, elastoplastic objects like plasticine are the most challenging objects, which show plasticity and elasticity under different interaction conditions. There are some works that aim to manipulate plasticine in simulation via RL [1], [2], but no observation available in reality is proposed. Detailed plasticine shapes are applied as observations, but such observations cannot be collected with real robots.

In order to generate transferable observations in simulation and prepare for RL, we include optical tactile sensors as end effectors. Optical tactile sensors [3], [4] provide tactile sensing signals with tactile images. The simulator *Tacchi* [5] is applied in this paper, which uses the Moving Least Squares Material Point Method (MLS-MPM) as the simulation method and Taichi [6], a parallel programming language for high-performance numerical computation. Following [1], this paper exploits the von Mises yield criterion [7] in elastoplastic property modeling. We also design observations and rewards for RL. Experimental results show that during designed behaviors, the rewards and observations change, which is the preliminary preparation for RL.

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II. Simulation Method

This paper uses Tacchi as the simulator. The application of MLS-MPM and Taichi endows Tacchi with the ability to simulate deformation with a low computational cost. This method represents objects with particles and defines an imaginary grid for interaction simulation, as shown in Figure 1.

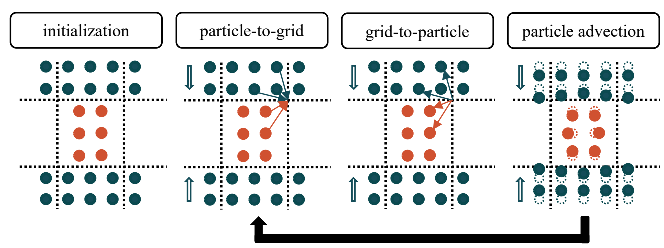

Fig. 1. The simulation process of MLS-MPM. Two gel layers (represented as blue particles) are controlled to press against a plasticine cube (represented as red particles). The intersection points of the black dotted lines are grid nodes.

MLS-MPM includes four steps: *initialization*, *particle-to-grid*, *grid-to-particle*, and *particle advection*. In *initialization*, the grid and particles including object information like mass and deformation gradient are initialized. Then, each grid node collects object information from nearby particles in *particle-to-grid*. After that, each particle collects object information from nearby grid nodes in *grid-to-particle*. The two steps above simulate the particle interaction. Finally, in *particle advection*, the particles move according to their velocities. The deformed gel layer surface is reconstructed making use of the particles in the top layer representing the elastomer, and the optical method in [8] renders the surface depth maps into tactile images. All the details can be found in [5].

Considering the elastoplasticity of plasticine, we introduce the von Mises yield criterion [7] in the *grid-to-particle* step. Specifically, this method determines whether a particle deforms in an elastic or plastic way. Suppose that F is the particle deformation gradient. The trial Hencky strain σ is derived by singular value decomposition $F = U\sigma V$. In this case, the von Mises yield criterion is

$$\delta\gamma = \|dev(\sigma)\| - \frac{\sigma_y}{2\mu}, \tag{1}$$

where $dev(\sigma) = \sigma - \frac{tr(\sigma)}{3}I$; σ_y denotes the yield stress parameter defined by the material property, 100 in this work based on trial and error. This criterion determines the final Hencky strain and deformation gradient:

$$F = \begin{cases} U\sigma V, & \delta\gamma \leq 0, \\ U(\sigma - \delta\gamma\frac{dev(\sigma)}{\|dev(\sigma)\|})V, & \delta\gamma > 0. \end{cases} \tag{2}$$

III. RL Preparation

In this section, the RL environment is built, and tactile images are provided as observations. Two tasks are proposed as the basic manipulation behaviors, which are reposition and squeeze, and rewards are designed according to these tasks.

The simulation environment is shown in Fig. 2. In the experiment, two optical tactile sensors are controlled to manipulate plasticine, as shown in Fig 2-(A). Tacchi only includes two gel layers and plasticine in the simulation, as shown in Fig 2-(B). The two sensors gently touch the plasticine in the initial situation.

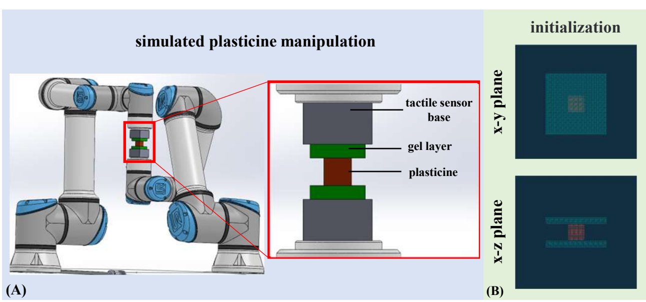

Fig. 2. (**A**): Plasticine manipulation diagram. Two optical tactile sensors mounted on robot arms are applied as end effectors. A plasticine cube is held and manipulated by these sensors. (**B**): Initial simulation. This diagram is the plasticine and gel layer simulation corresponding to (**A**). Red particles represent the plasticine, and green particles represent the gel layers.

The desired situations of the two tasks are shown in Fig. 3-(A) and (B). In the *squeeze* task, two sensors are moved along the z-axis, and the height of the plasticine achieves the desired value. The reward will be the opposite value of the distance between the current and desired heights. In the *reposition* task, the top sensor is moved on the x-y plane, and the plasticine will be moved to the desired position. The reward will be the opposite value of the Euclidean Distance between the current and desired positions. The observations are tactile images produced by Tacchi, as shown in Fig 3-(C).

IV. Experiments and Results

In the experiments, we control the sensors to move and show how the observations and rewards will change. In the *squeeze* task, the two sensors move close to each other and squeeze the plasticine, hence the height arrives at the desired value at first and then continues decreasing. In the *reposition* task, the upper sensor is controlled to move to the upper right. In this case the plasticine will first reach the desired position and then get away from it. The rewards and observations during these two manipulations are shown in Fig. 4. All the experiments are taken in simulation.

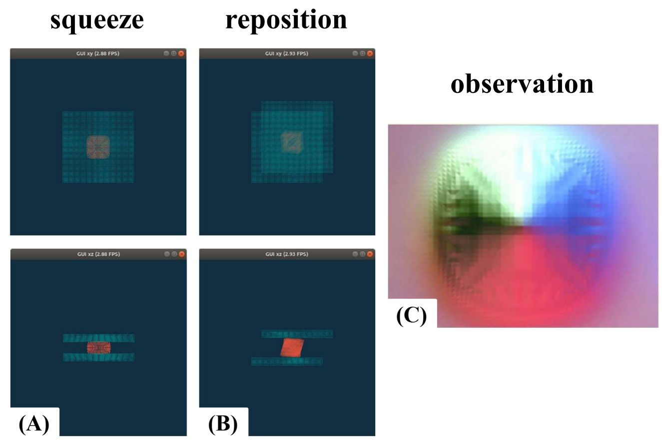

Fig. 3. The desired situations of the task reposition (**A**) and squeeze (**B**). (**C**): Tactile images are used as the observations.

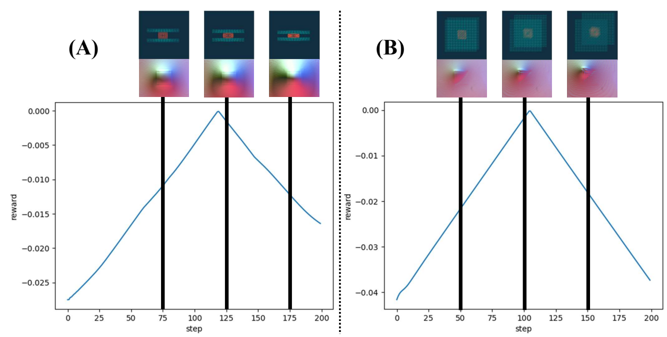

Fig. 4. The reward change, observations and deformations during the manipulation for *squeeze* (**A**) and *reposition* (**B**) tasks.

In Fig. 4, both of the rewards improve at first since the simulation environments are getting close to the desired situation, but then the rewards decrease. The observations reveal the change of various interactions. To this end, the experimental results show that this simulation environment and RL implementations are proper for future RL works.

V. Conclusion and Future Work

This paper creates a plasticine manipulation simulation environment whose observations are transferable to reality. Tacchi is utilized as the simulator since it can include elastic and elastoplastic objects in the simulation, and the von Mises yield criterion is used in plasticine modelling. With the results of rewards and tactile images as observations in preliminary tasks *squeeze* and *reposition*, we show the potential of using the proposed simulation environment to benchmark the RL algorithms for the plasticine manipulation task.

In the future, we will attempt to apply other tactile information like tactile flows as observations for RL. Some complex tasks, like kneading plasticine into a cylinder or sphere, will also be considered. Future work may also use the manipulation strategy obtained from the simulation environment in real world experiments.

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