A Telemanipulation Suite for Deformable Object Manipulation

Bonggyeong Park, Chanyoung Ahn, and Daehyung Park†

KAIST, Daejeon, Korea
{iampbk, coldyoung, daehyung} @ kaist.ac.kr

Abstract

Our aim is to create a human-expert manipulation dataset of deformable objects toward learning deformable manipulation. However, the data collection is challenging due to the limited sensing capability against to the high number of degree-of-freedom and complicate deformation/contact of soft bodies. Further, the self occlusion restricts the observation in grasping. In this work, we introduce a haptic-telemanipulation suite by adopting a haptic glove with a state-of-the-art physics simulator, IsaacGym from NVIDIA. The suite enables users to obtain realistic visual-and-tactile feedback as well as collect any part of object states while teleoperating a robotic gripper. We evaluate the suite by building one hundred demonstrations of dataset given five deformable objects. To show feasibility of our framework, we performed 108 times of pick-up experiments with five types of deformable objects, showing the experiment success rate of 93% within an average task completion time of 16.6 seconds. The result shows the proposed suite works for collecting human demonstrations toward learning for DOM.

1. Introduction & 2. Method

1. Introduction

We present a problem of creating deformable object manipulation (DOM) dataset toward learning dexterous manipulation skills from human experts. However, the dataset requires observing the state of a deformable object during the human demonstrations, though the limited sensing capability restricts recording detail such as the high degree-of-freedom (DoF) structure, the complicate deformation, and the precise contact of soft bodies. To resolve the incomplete sensing in demonstrations, we need a new data-collection method that is a task-and-object agnostic framework and also does not intervene the interaction between a human expert and a target object for the integ-rity of the dataset. We propose a virtual reality-based telemanipulation suite that allows an expert hand to manipulate simulated deformable objects while recording complete observations via a state-of-the-art deformable physics simulator, IssacGym from NVIDIA. The suite consists of telemanipulation and data-collection components. The former aims to transfer the real hand movement, observed via a haptic glove (i.e., SenseGlove DK1), to a simulated gripper (i.e., Robotiq 2F-85) by retargeting configurations. The latter records the gripper, the object, and their interaction states precisely simulating with the FleX physics engine.

2. Method

The proposed telemanipulation suite allows a human operator to grasp a simulated deformable object in Issac-Gym environment via master-slave robotic grasp system. The master device is an exoskeleton glove that can sense the 4-DoF movement of the human fingers and return force /haptic feedback to the fingers. The slave device is a simulated 2-DoF parallel-jaw gripper that can sense the finger-tip contact and grasp deformable objects.

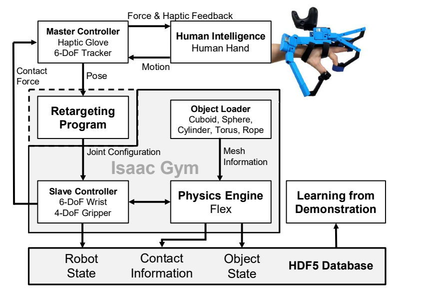

Fig. 1 Overall architecture of the proposed telemanipulation suite.

We retarget the master wrist pose but also its pinch-grasp motion. O and O' represent global frame of real world and simulation, respectively.

$$\overbrace{T^{O'}_{slave,t+1}}^{Slave\ Motion} = \overbrace{T^{O'}_{O}}^{Offset} \cdot \overbrace{T^{O}_{master,t}}^{Tracker\ Motion} \cdot \overbrace{T^{master}_{slave,t}}^{Human\ Motion}$$

Our framework recalls the state data from the interactions between objects and the gripper. Table shows the data our framework stores in the binary data format HDF5 database.

Category	Detail	Type	Unit
Pre-defined State			
Object Initial Pose (Pre-defined local frame)	Object Position	$FloatArray[3]$	m
	Object Orientation (Quaternion)	$FloatArray[4]$	–
Object Property	Density	$Float$	kg/m^3
	Elastic Modulus E	$Float$	Pa
	Poisson's Ratio ν	$Float$	–
Object Mesh Information	Triangle Mesh Element	$IntArray[N_1, 3]$	–
	Tetrahedron Mesh Element	$IntArray[N_2, 4]$	–
Time-series State			
Simulation	Time	$Float$	sec
Object State	Node Position $\vec{P}(N_3, 3)$	$FloatArray[N_3, 3]$	m
	Force on Node	$FloatArray[N_3, 3]$	N
	Von-mises Stress on Triangle Element	$FloatArray[N_1]$	Pa
Gripper State	Wrist Position	$FloatArray[3]$	m
	Wrist Orientation (Quaternion)	$FloatArray[4]$	–
	Gripper Tip Distance d	$Float$	m
	Normal Force on the Gripper Tip	$Float$Array[2]	N

Table. 1 Detailed description of data. $N_1, N_2,$ and N_3 are the number of edges, tetrahedron elements, and nodes of the object finite element mesh, respectively.

3. Result

3.1. Experiment

To evaluate the feasibility of the telemanipulation framework, we collected one hundred demonstrations from human experts with five objects each having four elastic modulus $E = \{10^4, 10^5, 10^6, 10^7\}$.

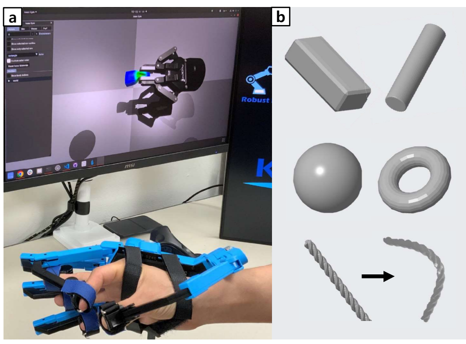

Fig. 2 A capture of telemanipulation task with five deformable objects.

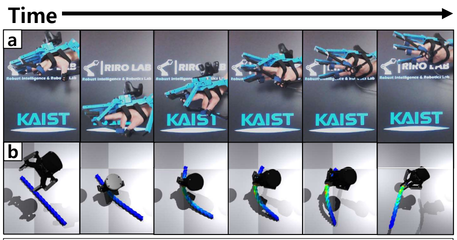

Fig. 3 A sequence of human demonstrated actions for pick-up task.

The careful movement of the gripper is the result of absorbing expert guidance, meaning that a learning agent could use our data for the learning from demonstration, which aims to transfer human policy to the agent. The expert performs pinch-grasping to pick up the object. As the gripper tip distance decreases, the gripper begins to apply force to the object, deforms the object, and causes an increase in contact force and stress. The framework transfe-rs the contact force to the haptic glove, which operates tendons and motor vibration controllers for the force-haptic feedback.

3.2. Result

Table 2 shows the evaluated success rate of simulated object pick-up tasks. The average success rate is 93% for the 108 times trials, with an average task completion time of 16.6 seconds. However, the success rate decreases as the elastic modulus decrease due to the slippage between the soft object and the gripper. As the elastic modulus decreases, the gripper easily deforms objects even with smaller contact force. Therefore, the gripper hardly applies enough friction force corresponding to object weight. This is why DOM is challenging compared to that of rigid bodies. However, our framework provides the acceptable manipulation environme-nt, even for soft objects. For example, object with elastic modulus $E = 10^4$ (tofu-like stiffness), the expert completed the task with the success rate of 80% within 16.7 seconds.

Elastic Modulus	Cuboid	Sphere	Torus	Cylinder	Rope	Average
10^4	0.83	1	0.63	0.83	-	**0.8**
10^5	0.83	1	0.67	1	1	**0.87**
10^6	1	1	1	1	1	**1**
10^7	1	1	1	1	1	**1**
Average	**0.91**	**1**	**0.78**	**0.95**	**1**	**0.93**

Table. 2 The success rate of pick-up experiment.

Conclusions

We proposed a haptic-telemanipulation framework to create a human-expert manipulation dataset for learning deformable object manipulation skills. We retargeted the simulated slave 4-DoF gripper and 6-DoF wrist robot using the haptic glove (i.e., SenseGlove DK1 with 4-DoF per finger) and 6-DoF HTC VIVE Tracker, respectively. We performed pick-up experiments, lifting the object from the floor to a certain height. We stored sufficient information to describe the simulation state and analyzed the data to show that the data potentially contains human intelligence for the DOM. We evaluated that the average experiment success rate is 93%, taking an average task completion time of 16.6 seconds. In the future, we will generalize the framework further using various slave robots and perform offline learning of deformable object manipulation using the collected dataset.