(Writing Sample)

# A Reinforcement Learning Testbed for Deformable Object Manipulation using Tactile Sensing

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**Abstract** We aim to create a simulated testbed for training and assessing deformable object manipulation skills. This testbed requires tactile data to detect occluded deformation to acquire skills. In this work, we introduce a tactile testbed, DetactGym, with custom-built tactile sensors. We implement tactile sensors as a combination of a rigid trigger and a force-reading part to address the IsaacSim simulator's inability to read contact forces in deformable. The trigger transmits the contact force to the sensor upon interaction with the target deformable. We highlight the effectiveness of tactile information over visual cues in handling deformable objects while minimizing deformation.

**Keywords:** Testbed, Deformable Object Manipulation, Reinforcement Learning

## 1. Introduction

We aim to develop a simulation testbed for training and acquiring deformable object manipulation (DOM) skills. The learning process requires tactile information to ensure comprehensive observations when deformations occur in obscured regions of the objects in hand. However, most testbed developments focus on vision-based DOM [1] or tactile-based rigid body manipulation [2].

To overcome the observation limit, we introduce DetactGym built on the NVIDIA IsaacSim simulator. Our gym environment includes specialized tactile sensors, deformable objects, sensing modules, and a challenging environment that demands tactile observations.

We design simulated tactile sensors for gripper tips, each containing six taxels capable of detecting three-axis force, as depicted on the left side of [Fig 1]. Each taxel comprises a *sensor* and a *trigger*, where the *sensor* detects the force a deformable object presses against the trigger. We use taxels because measuring contact force against deformables is not directly available in IsaacSim's contact APIs.

Additionally, DetactGym offers a task for manipulating soft objects with a tactile observation and provides sensing modules to compute raw sensing data. We demonstrate the capability of our testbed to facilitate learning skills in environments with tactile sensors using reinforcement learning (RL) techniques.

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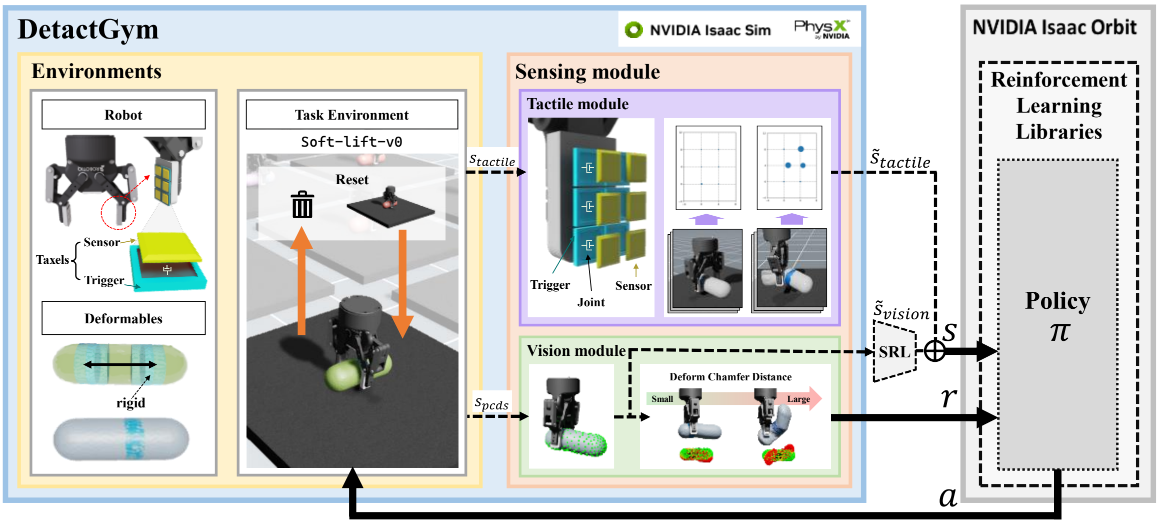
## 2. Method

We illustrate an overview of our testbed as shown in [Fig. 1]. The testbed consists of assets, a task environment, and sensing modules.

1) **Assets:** DetactGym features a simulation of a Robotiq 2F85 gripper equipped with tactile sensors and heterogeneous deformables. These tactile sensors consist of six $(2 \times 3)$ taxels, each capable of detecting three-axis force at the tips of the gripper. Consequently, the tactile sensors provide 36 data points per physics step, operating at a frequency of $200\ Hz$. Each taxel comprises *sensor* and *trigger* components to overcome the inability to directly measure contact forces against deformables using contact APIs provided by IsaacSim. The *sensor* of a taxel measures its contact force against the *trigger* that acts as a rigid proxy object, delivering the same contact force acted from a deformable to the *sensor*. The *trigger*'s geometry and a prismatic joint between a *sensor* and a *trigger* prevent the *sensor* from protruding. DetactGym also includes five heterogeneous deformables, including soft objects with rigid parts.
2) **Task Environment:** DetactGym parallelizes the deformable manipulation environment to accelerate RL. IsaacSim lacks support for instantaneous rotation or deformation, resulting in the instability and unreliability of resetting soft objects' configurations. This interference impedes the learning process and results in simulation instability. Therefore, DetactGym respawns assets upon each reset. This approach ensures the initialization of the objects while simultaneously randomizing properties such as position, orientation, and size in each




[Fig. 1] The overall framework of DetactGym. DetactGym integrates a tactile sensor with robot states and offers an interface that provides point cloud data for deformable manipulation. DetactGym further delivers latent vectors obtained through external state representation learning (SRL) model. The system is compatible with reinforcement learning (RL) policies and algorithms.

environment.

3) **Sensing Module:** DetactGym features sensing modules for both tactile and vision. The tactile module computes the average of tactile data points over the preceding three steps since tactile data are inherently noisy due to the sensitivity of each tactile datum to collisions between the sensor and trigger, as well as the movement of the gripper. This module regularizes the data, mitigating the impact of abrupt data fluctuations.

The vision module supports the handling of raw point clouds. This module provides the *deform chamfer distance metric*, a measure of object deformation through the point clouds. The *deform chamfer distance* is the normalized chamfer distance calculated after eliminating the difference between the initial and current pose from the point clouds.

## 3. Experiments

We introduce the *soft-lift-v0* task, aiming to train an agent to lift a soft object with minimal deformation. The action space of the agent is the change in the x-axial displacement of the gripper. The reward in the final state is (threshold - *deform chamfer distance*) × (pick up an object).

We perform training on the *soft-lift-v0* to confirm the feasibility of DetactGym using RL. We train two cases as observations: only vision and only tactile, maintaining identical Markov decision process (MDP) conditions, excluding state. The training spans 20,000 steps across four environments, utilizing an NVIDIA A6000 GPU. The results are in [Table 1].

[Table 1] Evaluating success rate of *Soft-lift-v0* with 100 episodes in tactile, and vision observations.

| Rate of Success (%) | Tactile | Vision |
|---|---|---|
| PPO | 88.0 % | 72.0 % |

The result demonstrates that the *soft-lift-v0*'s success rate with tactile sensors exceeds that with vision by over 16 percent, as shown in [Table 1]. This result presents the tactile sensor's ability to detect deformations that outperform the vision sensor during grasping.

## 4. Conclusion and Future Works

In conclusion, DetactGym enables learning skills in *soft-lift-v0* with visual or tactile sensors through RL. We highlight the effectiveness of tactile information over visual cues in manipulating deformable while minimizing deformation.

For future works, we plan to develop a complex environment that expand the action space and a diverse range of randomized assets to assess tactile sensors' benefits on real-world objects.

## References

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