Adaptive contact-rich manipulation through few-shot imitation learning with tactile feedback and pre-trained object representations

Chikaha Tsuji[1], Enrique Coronado[2], Pablo Osorio[3] and Gentiane Venture[1,2]

***Abstract*—In learning-based contact-rich tasks, careful force control is essential to adapt to environmental changes due to limited demonstration data and the gap between training and deployment conditions. This is particularly vital in a wiping task as manipulating soft and deformable objects (e.g., sponge), where adaptations in applied force are demanded according to the wiping surface height and the sponge properties. To solve this problem, we introduce a method that combines real-time tactile feedback with pre-trained object representations, enabling robots to adjust to unseen surface height and object properties. Tested on real hardware, the approach successfully adapts to changes in the manipulating environment by analyzing force trajectories, showcasing a significant advancement in adaptability.**

***Index Terms*—few-shot imitation learning, force-based contact-rich manipulation, object representation**

I. Introduction

In recent years, robots have been regarded as potential replacements for human labor, with expectations for their roles expanding into complex and diverse tasks. However, it is impractical to pre-program every task, leading to increased attention towards imitation learning [6]. Imitation learning enables humans to teach robots complex behaviors intuitively, without complex programming. However, challenges remain, such as the need for extensive human demonstration data and the discrepancies between demonstration and execution environments [5]. These difficulties necessitate robots not merely mimicking but adapting to new environmental conditions even from a limited number of demonstration data. Especially a contact-rich wiping task requires careful force control according to the wiping surface height and the sponge's physical properties.

Therefore, in this paper, we address the challenge – *Could robots learn a versatile manipulation policy via few-shot imitation learning capable of adapting to environmental changes: the height of manipulating surface and the physical properties of manipulated objects?*

A. Related Works and Contribution

In the field of few-shot imitation learning, [7] and [4] leveraged large amounts of other/similar tasks' data to acquire task embeddings and adapted to downstream tasks with limited numbers of demonstrations. Specifically, in the context of learning-based contact-rich tasks, [9] used Gaussian mixture models and variable impedance control, whereas [10] took advantage of both imitation learning and reinforcement learning. Moreover, multiple studies addressed pre-training representations for manipulation [8], [3]. Aoyama et al. adopted a semi-supervised Learning from Demonstration (LfD) framework and successfully controlled the force according to the object properties with few-shot imitation learning [1]. However, they controlled the wiping motions in an open-loop manner, thus the approach lacked the ability to adapt to environmental changes, such as variations in wiping surface height.

To address this limitation, **we propose a framework that combines pre-training to represent the physical properties of manipulated objects and real-time feedback of time-series tactile information, enabling the robot's adaptation to environmental changes from a small number of human demonstrations**. We validate our approach on real hardware by altering the height of the wiping surface and the physical properties of the sponge as variable environmental factors in a wiping task, showcasing the ability to adapt to unseen environmental conditions by analyzing force measurements.

II. Methods

The proposed method consists of two steps: a pre-training step using simulations and a training step using a real robot before being deployed (Fig. 1), each detailed below.

A. Pre-training step

We pre-train the sponge properties encoder ϕ_{sponge} on unlabeled data $D_{\text{sim}} = \{(\tau^{\text{exp}})_1, \dots, (\tau^{\text{exp}})_M\}$ to capture the sponges' physical properties as the latent space covering a wide range of the underlying distribution. We use a self-supervised learning framework inspired by [1] but with a modified architecture.

B. Training step

We train the motion trajectory decoder θ_{traj} and the tactile feedback loop $\phi_{\text{tactile}} - \theta_{\text{height}}$ on unlabeled data $D_{\text{real}} = \{\tau^{\text{exp}}\}$ and few-shot human demonstration data $D_{\text{demo}} = \{(x^{\text{demo}}, \Delta h^{\text{demo}}, \tau^{\text{demo}})_1, \dots, (x^{\text{demo}}, \Delta h^{\text{demo}}, \tau^{\text{demo}})_N\}$.

1) motion trajectory decoder θ_{traj}: We train the wiping motion trajectory decoder θ_{traj} using LfD [1] to generate the wiping motion according to the manipulated sponge properties.

2) Tactile feedback loop: We train a tactile feedback loop $\phi_{\text{tactile}} - \theta_{\text{height}}$ composed of the tactile encoder ϕ_{tactile} and the end-effector's vertical position decoder θ_{height} to obtain a control input of the next time step's height displacement according to the contact state and the manipulated sponge.

The tactile feedback loop takes the force-torque history of demonstration $D_{\text{demo\_ft}} = \{\tau^{\text{demo}}_{\text{t-4}}, \dots, \tau^{\text{demo}}_{\text{t}}\}$ and unlabeled data $D_{\text{real}} = \{\tau^{\text{exp}}\}$ of the manipulated sponge as inputs and

[1] The University of Tokyo, Japan
[2] National Institute of Advanced Industrial Science and Technology, Japan
[3] Tokyo University of Agriculture and Technology, Japan

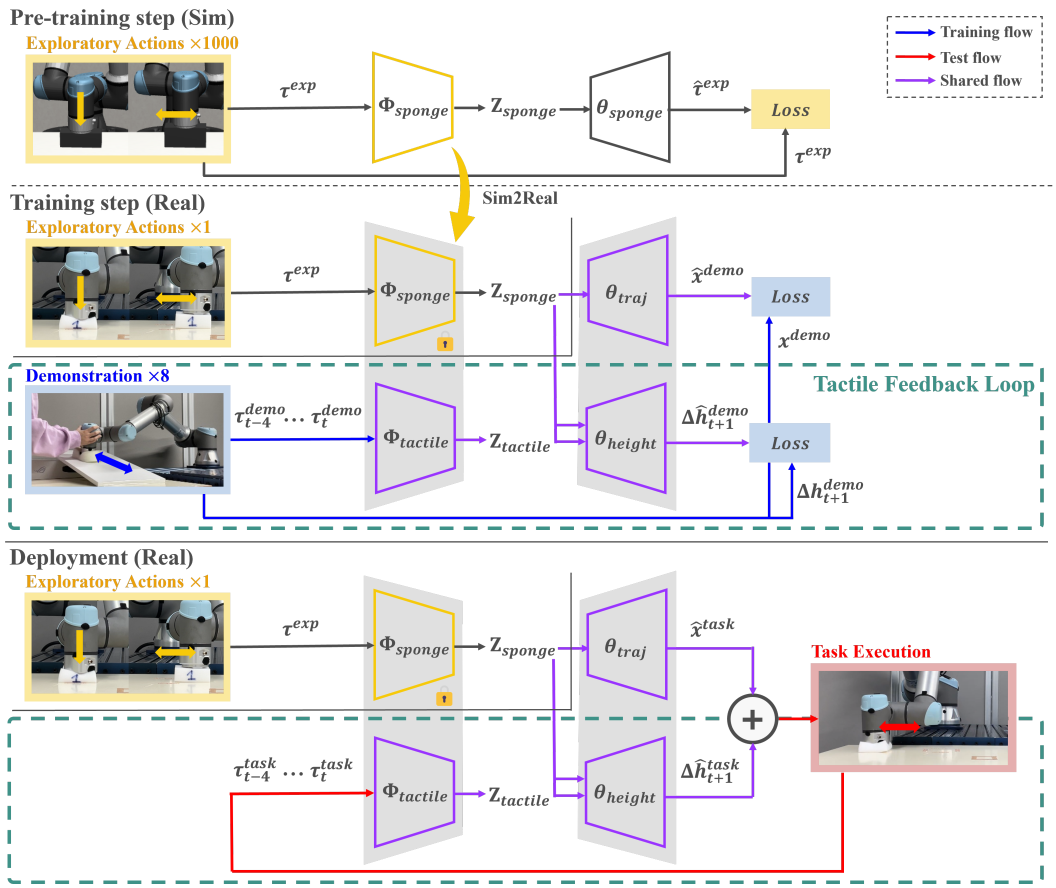

Fig. 1. Overview of our proposed framework. First, we pre-train the sponge properties encoder ϕ_{sponge} using simulated unlabeled data (Pre-training step II-A). Then, we train the motion trajectory decoder θ_{traj} and the tactile feedback loop $\phi_{\text{tactile}} - \theta_{\text{height}}$ to obtain the wiping policy with the active inference of applied force using few-shot human demonstration data (Training step II-B). Finally, we deploy the acquired policy on real robot hardware (Deployment II-C).

outputs the next time step's vertical displacement $\Delta\hat{h}^{\text{demo}}_{\text{t+1}}$. The tactile encoder ϕ_{tactile} consists of 2 layers of TCN [2] and the end-effector's vertical position decoder θ_{height} consists of 2 fully connected layers. We adopt the Mean Squared Error and train for 2000 epochs.

C. Deployment

In the task execution, the robot performs a wiping motion by combining offline (x, y) and online (z) motion execution. The robot plays back the generated planar motion in the (x,y) plane offline. The tactile feedback loop actively inferences the next vertical position $\Delta\hat{h}^{\text{task}}_{\text{t+1}}$ from the previous∼current force and torque data $D_{\text{task\_ft}} = \{\tau^{\text{task}}_{\text{t-4}}, \ldots, \tau^{\text{task}}_{\text{t}}\}$, and adapts online.

III. Experiment Setup

A. Wiping task and robot

To illustrate our proposition, we use a contact-rich wiping task in which the robot has to adapt its wiping motion to the wiping surface height and the manipulated sponge's physical properties. We prepare three heights of a table (low, high, and slope) and three sponges (low damping, stiff, and normal).

We use a 6 DoF UR5 e-series robot arm with a 6-axis force-torque sensor and a sponge attached to its end-effector for both simulation (robosuite [11]) and real robot experiments.

B. Dataset

The datasets are pre-processed before training; we apply a Butterworth low-pass filter offline to unlabeled data and online to force-torque trajectories of demonstrations. Subsequently, we normalize all data to [0.0, 0.9].

1) Unlabeled data: The robot performs two pre-defined exploratory actions [1]. We record the 3-axis force and torque for $4s$ at a frequency of $100Hz$ while performing exploratory actions to obtain force-torque trajectory $\tau^{\text{exp}} \in \mathbb{R}^{400\times 6}$. We collect 1000 unlabeled data in simulation for pre-training by randomizing the sponge's friction, stiffness, and damping. For training, we collect 1 demonstration unlabeled data of a normal sponge. *'Normal'* refers to common friction, stiffness, and damping properties.

2) Demonstration dataset: A human demonstrator kinesthetically performs the desired wiping motion by moving the robot's end-effector in free drive mode. The demonstrator wipes the inclined table (slope) applying as much force as possible. We collect 8 demonstrations using a normal sponge

TABLE I

EXPERIMENTAL RESULTS: CHANGES IN HEIGHT

Table height	Force*	Baseline			Proposed		
		Ratio	*Average**	*Integral**	*Ratio*	*Average**	*Integral**
Low	-17.2	72%	-1.2	-28.9	100%	-21.0	-525.3
High	-17.2	68%	-5.9	-147.1	100%	-21.0	-524.2

*Force, Average in N, Integral in N·Timestep

TABLE II

EXPERIMENTAL RESULTS: CHANGES IN SPONGE PROPERTIES

Sponge properties	Force*	Baseline			Proposed		
		Ratio	Average*	Integral*	Ratio	Average*	Integral*
Normal	-17.2	72%	-1.2	-28.9	100%	-21.0	-525.3
Low damping	-29.1	0%	0.3	8.6	100%	-28.3	-707.5
Stiff	-65.6	0%	2.2	52.7	100%	-31.9	-796.6

*Force, Average in N, Integral in N·Timestep

with varying wiping speeds. We record the robot's end-effector's position, force and torque in the (x, y, z) axis at a rate of $2.5Hz$ for $10s$ to obtain motion trajectory $x^{\text{demo}} \in \mathbb{R}^{25\times 2}$ (2 absolute positions in (x, y) axis), vertical position displacement trajectory $\Delta h^{\text{demo}} \in \mathbb{R}^{25}$ (vertical displacements from the previous time step), and force-torque trajectory $\tau^{\text{demo}} \in \mathbb{R}^{6\times 25}$.

IV. Results And Discussions

To evaluate our method, we experimented with the robot with varying heights of the wiping table (IV-A) and sponges manipulated (IV-B). For each verification, we compared the contact with the table by examining the ratio of time steps in which the sponge contacted a table. Next, we examined the force applied to the sponge to compare whether the robot *'wiped'* with the sponge. Specifically, we used the average vertical force applied to the sponge and its integral.

A. Verification of the ability to adapt to changes in height

We varied the table height (low and high) from the demonstration setup (slope) to evaluate our proposed method's ability to adapt its wiping motion to wiping surface heights unseen during training. The results are shown in Table I and Fig. 2.

To adapt wiping motions to changes in the wiping surface height, the robot should apply the same force to the sponge regardless of the height. With the same sponge, the robot should wipe with as much force as possible. With the baseline, the sponge was 70% of the time in contact with the table, and the average force applied was 3 to 10 times smaller than expected, showing that the robot was not *'wiping'* adequately. Additionally, the average force applied differed with the table height, indicating an inability to adapt to changes in the height of the wiping surface. With the proposed method the sponge was always in contact with the table and the *'wiping'* was successful both when the height was low and high, as the robot maintained an appropriate average force on the sponge. Furthermore, the force applied did not vary much whether a table was low or high, indicating the ability to adapt to the height changes.

B. Verification of the ability to adapt to changes in sponge

We varied the sponge properties (low damping and stiff) from the sponge used in demonstrations (normal). The height of the table is the same as the low condition described in IV-A. The results are shown in Table II and Fig. 2.

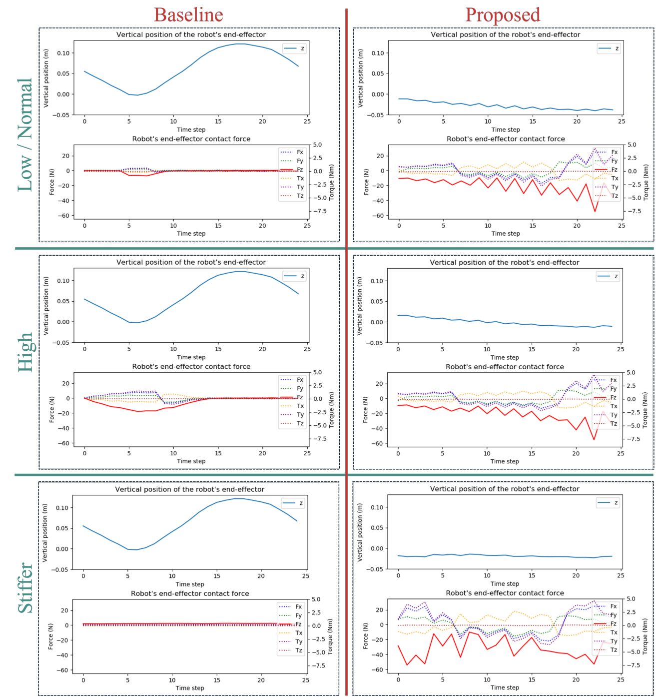

Fig. 2. Plots of robot end-effector's vertical position and force-torque profiles in representative cases comparing our proposed method with baseline.

Adapting the wiping motions to changes in the sponges' properties means adjusting the force applied to the sponge. In Table II, the three sponges are ordered by absolute vertical force applied during the exploratory actions. The average force applied during the experiments should match this order. When the sponge was changed, the baseline method failed to maintain contact with the table (ratio 0%), and the average force was very small, showing that the robot was not *'wiping'*. Additionally, the integral of the force turned positive when changing the sponge due to the gravity force pulled by the sponge's weight. Therefore, the baseline is unable to adapt to unseen sponges. On the other hand, the proposed method successfully keeps contact at all times and applies an average force comparable to that expected, indicating that a robot can adapt to unseen sponge properties.

V. Conclusion

This work tackles the challenge of robots adapting to environmental changes in manipulating deformable objects in contact-rich tasks with few human demonstrations. Our method combines real-time tactile feedback with pre-trained object representations. Focusing on a wiping task, we varied table heights and sponge properties. Experimental results show that the robot adapts to unseen manipulating surface height and object properties with our method. In the future, we aim to enable robots to learn the physical properties of deformable objects from a limited number of data, eliminating the need for extensive pre-training to avoid the challenging task of simulating their dynamics.

References

[1] M. Y. Aoyama, J. Moura, N. Saito, and S. Vijayakumar. Few-shot learning of force-based motions from demonstration through pre-training of haptic representation. In *Proc. of the 2024 Conference on IEEE International Conference on Robotics and Automation*, 2023.

[2] S. Bai, J. Z. Kolter, and V. Koltun. An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. *arXiv:1803.01271*, 2018.

[3] Y. Bengio, A. Courville, and P. Vincent. Representation learning: A review and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35:1798–1828, Aug. 2013.

[4] M. Du, S. Nair, D. Sadigh, and C. Finn. Behavior retrieval: Few-shot imitation learning by querying unlabeled datasets. In *Proc. of the 2023 Conference on Robotics: Science and Systems*, 2023.

[5] Y. Duan, M. Andrychowicz, B. Stadie, O. Jonathan Ho, J. Schneider, I. Sutskever, P. Abbeel, and W. Zaremba. One-shot imitation learning. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc., 2017.

[6] A. Hussein, M. M. Gaber, E. Elyan, and C. Jayne. Imitation learning: A survey of learning methods. *ACM Computing Surveys (CSUR)*, 50(2):1–35, 2017.

[7] S. James, M. Bloesch, and A. J. Davison. Task-embedded control networks for few-shot imitation learning. In A. Billard, A. Dragan, J. Peters, and J. Morimoto, editors, *Proc. of The 2nd Conference on Robot Learning*, volume 87 of *Proc. of Machine Learning Research*, pages 783–795. PMLR, 29–31 Oct 2018.

[8] A. Merckling, A. Coninx, L. Cressot, S. Doncieux, and N. Perrin. State representation learning from demonstration. In *Machine Learning, Optimization, and Data Science*, page 304–315. Springer Int. Pub., 2020.

[9] L. Rozo, D. Bruno, S. Calinon, and D. G. Caldwell. Learning optimal controllers in human-robot cooperative transportation tasks with position and force constraints. In *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, pages 1024–1030, 2015.

[10] Y. Wang, C. C. Beltran-Hernandez, W. Wan, and K. Harada. Robotic imitation of human assembly skills using hybrid trajectory and force learning. In *Proc. of the 2021 Conference on IEEE International Conference on Robotics and Automation*, pages 11278–11284, 2021.

[11] Y. Zhu, J. Wong, A. Mandlekar, R. Martín-Martín, A. Joshi, S. Nasiriany, and Y. Zhu. robosuite: A modular simulation framework and benchmark for robot learning. In *arXiv preprint arXiv:2009.12293*, 2020.