Bi-Touch: Bimanual Tactile Manipulation with Sim-to-Real Deep Reinforcement Learning

Yijiong Lin, Alex Church, Max Yang, Haoran Li, John Lloyd, Dandan Zhang, Nathan F. Lepora

I. INTRODUCTION

BIMANUAL robotic manipulation is a useful and natural way of manipulating large, unwieldy or coupled objects due to the better manoeuvrability, flexibility and a larger workspace compared to single-arm settings [1]. Furthermore, the higher dimensionality of the dual-arm state-action space can enable more realistic tasks for real-world applications, particularly when tactile sensing is leveraged to complement vision [2]. However, there are challenges in applying bimanual touch: (1) dual-arm systems often introduce more complexity in terms of system integration and controller design [3], and (2) the high cost of existing dual-arm systems makes them less accessible to the research community. Moreover, while vision is commonly used as the primary sensing modality for bimanual manipulation, tactile sensing complements those aspects where vision is limited, such as enabling physically interactive control with soft contacts and ensuring robustness in scenarios where visual occlusion may occur [4].

The main contributions of this work are as follows:

1) We adapt and extend the Tactile Gym 2.0 [5] to a low-cost dual-arm tactile robot setting with three new contact-rich bimanual tasks: bi-pushing, bi-reorienting, and bi-gathering.

2) We introduce appropriate reward functions for these tasks and show that deep RL reaches satisfactory performance using only proprioceptive and tactile feedback. To improve the robustness of the policies for real-world applications, we improve the sim-to-real transfer for bi-reorienting and propose a novel goal-update mechanism (GUM) for bi-gathering.

3) We demonstrate that the bimanual policies learned in simulation can be transferred well to the physical dual-arm robot. We further demonstrate the generalizability and robustness of the learned policies by testing the system on unseen objects. Videos are available at https://sites.google.com/view/bi-touch/

II. METHODS

A. Accessible Dual-arm Tactile Robotic System

1) Desktop Tactile Dual-arm Platform: To facilitate affordable automation and lower the entry barrier, we develop a low-cost dual-arm tactile robotic system while keeping high accuracy, which is comprised of two industry-capable desktop robotic arms (Dobot MG400) with vision-based tactile sensors mounted at the wrists as end-effectors (Fig. 1c). The proposed platform is developed with the Tactile Gym 2.0 [5] simulation (Fig. 1a) for deep RL-based policy training (see Sec. II-C).

All authors are with the Department of Engineering Mathematics and Bristol Robotics Laboratory, University of Bristol, Bristol BS8 1UB, U.K. (email: {yijiong.lin, n.lepora}@bristol.ac.uk)

B. Sim-to-Real Deep RL Framework for Bimanual Tactile Robotic Manipulation

To apply the deep RL policies learned in simulation to the physical dual-arm tactile robotic system, we take a sim-to-real approach [6] consisting of three parts (shown in Fig. 1): **1)** An online agent training in simulation (Fig. 1a), where deep RL policies are learned in the Tactile Gym for three bimanual tactile robotic tasks (bi-pushing, bi-reorienting and bi-gathering) with observations comprising simulated tactile images and proprioceptive feedback. **2)** A real-to-sim domain adaption process where a translation model is learned to transfer real to simulated tactile images. **3)** A sim-to-real application with networks trained in the previous two parts, for transferring deep RL policies to the physical system.

C. Bimanual Tactile Manipulation Tasks

In this study, we propose three bimanual tactile control tasks to benchmark the aforementioned dual-arm tactile system: bi-pushing, bi-gathering and bi-reorienting.

1) Bi-Pushing: An advantage of dual-arm robots over single-arm robots is that they can move relatively large and unwieldy objects. The goal of this bi-pushing task is to move a large object on a planar surface collaboratively with two robot arms with end-effectors to achieve a sequence of goals along a given trajectory.

2) Bi-Reorienting: Reorienting an object with two arms is necessary when the object size exceeds the limit of what can be held by a gripper or a robot hand. The goal of this bi-reorienting task is for two robotic arms to reorient an object located at the workspace centre to a given target angle while keeping the object centre fixed in place. The dual-arm robot should reorient the object with gentle contact while keeping the end-effectors (TacTips) normal to the contact surface.

3) Bi-Gathering: Gathering objects together is a common behaviour in our daily life, from tidying our desks to moving and sorting packages in warehouses. The goal of this bi-gathering task is for the dual-arm robot to gather two objects together by pushing them towards each other on a planar surface. Thus, each end-effector of the dual-arm robot has to push an object towards a dynamically changing goal. To further explore the limit of the dual-arm tactile robot, we also introduce random perturbations to the objects during the gathering. Specifically, a random force is applied to an object's centre of mass at a random time step when training.

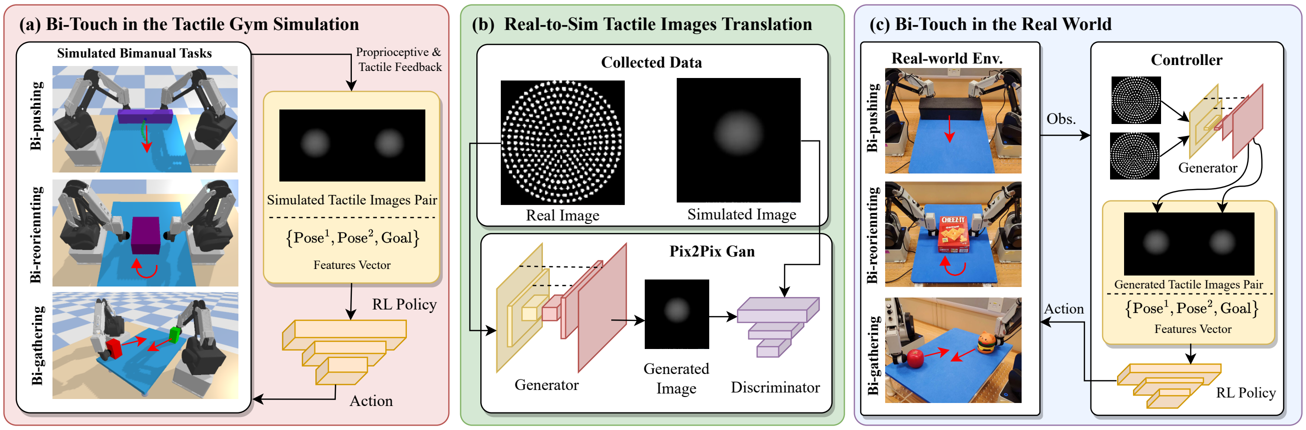

Figure 1. Overview of the proposed dual-arm tactile robotic system (Bi-Touch) with sim-to-real deep RL. a) Deep RL is applied to learn policies for three simulated bimanual tactile manipulation tasks (red arrows show desired displacements) using Tactile Gym. b) Real-to-sim tactile image generator learnt for the surface feature. c) The real-world evaluation feeds real tactile images through the generator into the RL policy concatenated with proprioceptive information.

III. Experiments and Results

A. Evaluations on the Bi-Touch in Simulation and Reality

An on-policy model-free deep-RL algorithm called Proximal Policy Optimization [7] is used to train policies in simulation for all three proposed bmanual tactile robotic tasks.

We obtained successfully trained policies in simulation for all three tasks. The bi-pushing is the easiest task to learn with a smooth learning curve and convergence at an early time step. The other two tasks have subtleties in learning that we describe below.

1) Bi-Pushing: The accuracy from 20 simulated tests of random trajectories is 12.3 ± 4.8 mm. And the accuracy from 20 real-world tests of random trajectories for the tripod box, the shuttle tube, and the loudspeaker are 14.2 ± 6.4 mm, 16.6 ± 7.7 mm, and 17.4 ± 8.1 mm respectively, compared to an overall distance travelled of 300-420 mm. The performances on all objects are similar despite notable differences in their contact shapes (e.g. flat, curved, and sloping surface), showing the generalization ability of the learned policy.

2) Bi-Reorienting: The average translation and orientation errors from 10 simulated tests are 10.2 ± 4.8 mm and $3.4 \pm 1.8°$ respectively. In reality, the robot achieved this task with most of the selected objects with translation error from 12.5 ± 5.3 mm to 19.5 ± 7.0 mm, and orientation error from $7.5 \pm 3.9°$ to $13.4 \pm 6.5°$, except the triangular prism where there was a problem with the sharp edge.

3) Bi-Gathering: Upon testing the policy trained under perturbations with the goal-update mechanism, the success rates are 100% with different perturbation times in each of 5 simulated tests. In reality, the robot successfully completed the bi-gathering task without perturbation in all sets of 10 trials for each object. Regarding the effect of perturbations, the robot completes the task at 100% success rate when the perturbation is applied twice or fewer times. The success rate decreases when the number of applied perturbations is increased for all pairs of objects, decreasing most for the irregular items (mug, triangular prism, foam toy and spam can).

IV. Discussion and Future Work

We developed a low-cost dual-arm tactile robot system called Bi-Touch for sim-to-real deep reinforcement learning based on Tactile Gym 2.0 [5]. The hardware includes two industry-capable desktop robot arms (Dobot MG400), each equipped with a low-cost high-resolution optical tactile sensor (TacTip) as end-effectors. We also designed a workspace configuration suited for three proposed bimanual tasks tailored towards tactile feedback and integrated into the Tactile Gym simulation methods and environments.

The performance of our low-cost sim-to-real deep RL dual-arm tactile robot system was evaluated in these three bimanual tasks in the real world. We introduced appropriate reward functions for these tasks in simulation, then investigated how these policies apply to the real world. The experimental results show that the developed dual-arm tactile system is effective for all tasks on real objects unseen in the simulation learning.

References

[1] C. Smith, Y. Karayiannidis, L. Nalpantidis, X. Gratal, P. Qi, D. V Dimarogonas, and D. Kragic. Dual arm manipulation—a survey. *Robotics and Autonomous systems*, 60(10):1340–1353, 2012.

[2] J. Hansen, F. Hogan, D. Rivkin, D. Meger, M. Jenkin, and G. Dudek. Visuotactile-rl: Learning multimodal manipulation policies with deep reinforcement learning. In *2022 International Conference on Robotics and Automation (ICRA)*, pages 8298–8304. IEEE, 2022.

[3] D. Kruse, J. T. Wen, and R. J. Radke. A sensor-based dual-arm tele-robotic system. *IEEE Transactions on Automation Science and Engineering*, 12(1):4–18, 2015.

[4] Jiaqi Jiang, Guanqun Cao, Jiankang Deng, Thanh-Toan Do, and Shan Luo. Robotic perception of transparent objects: A review. *IEEE Transactions on Artificial Intelligence*, pages 1–21, 2023.

[5] Y. Lin, J. Lloyd, A. Church, and N. Lepora. Tactile gym 2.0: Sim-to-real deep reinforcement learning for comparing low-cost high-resolution robot touch. volume 7 of *Proceedings of Machine Learning Research*, pages 10754–10761. IEEE, August 2022.

[6] A. Church, J. Lloyd, R. Hadsell, and N. Lepora. Tactile Sim-to-Real Policy Transfer via Real-to-Sim Image Translation. In *Proceedings of the 5th Conference on Robot Learning*, pages 1–9. PMLR, October 2021.

[7] J. Schulman, F. Wolski, A. Radford, and O. Klimov. Proximal policy optimization algorithms. *arXiv preprint:1707.06347*, 2017.