The Effect of Incorporating Motor Current Feedback in an Imitation Learning Policy for a Multi-DOF Robot

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Introduction

- Traditional imitation learning (IL) policies for contact-rich tasks rely mainly on joint position and trajectory data
- Recent research shows that incorporating force feedback significantly improves task success rates, with reported gains of 30–40% over position-only approaches
- Most hobbyist robot arms, including the SO-101, do not include dedicated force or torque sensors.
- Motor current signals, available from most servos, provide a low-cost way to estimate contact forces.
- Prior work demonstrates that grip force can be accurately estimated by running motor current signals through a regression model, resulting in minimal error.
- However, it remains unclear whether directly adding raw motor current signals to an imitation learning policy improves performance.

Hypothesis

If motor current feedback is added as an input to an imitation learning model, then the accuracy of the manipulation task improves.

Task

The task required the robot to pick up a cube placed at a fixed location in the workspace and move it to one of two designated target zones: left for soft (TPU) cubes and right for hard (PLA) cubes.

References

Zhao TZ, et al. (2023). "Learning Fine-Grained Bimanual Manipulation with Low-Cost Hardware." arXiv.

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Li Y, Hannaford B. (2017). "Gaussian Process Regression for Sensorless Grip Force Estimation of Cable Driven Elongated Surgical Instruments." IEEE Robotics and Automation Letters, 2(3):1312–1319.

Kobayashi M, et al. (2024). "ILBiT: Imitation Learning for Robot Using Position and Torque Information based on Bilateral Control with Transformer." arXiv.

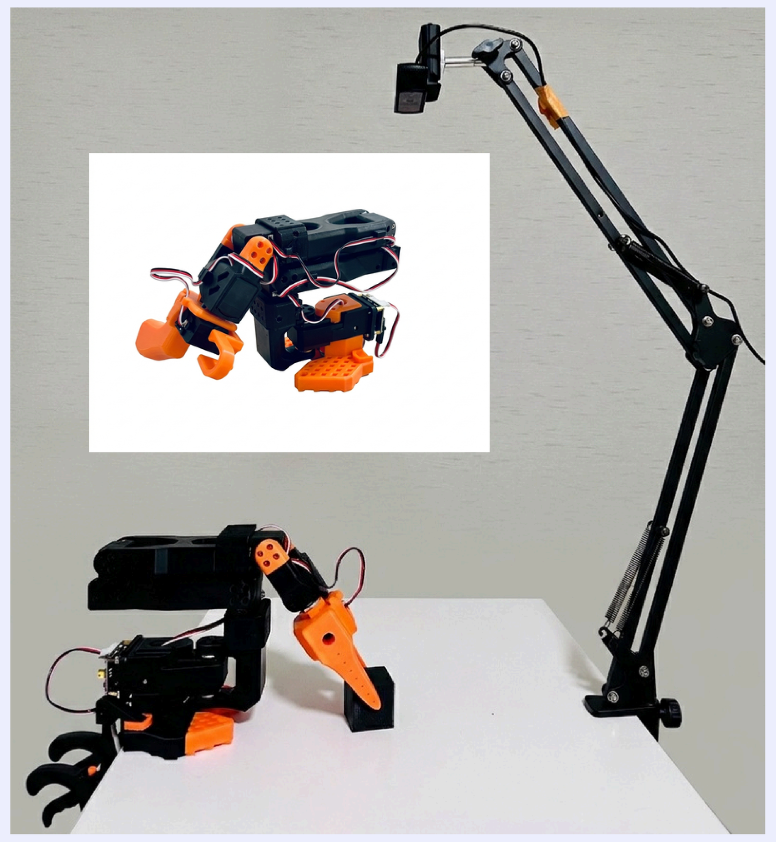

Figure 1: Training, inference, and teleoperation setup. Inset showing the leader robot arm.

Materials

- 2 SO101 robot arms (one leader, one follower)
- Logitech C920x webcam
- LeRobot (robotics library by Hugging Face)
- Google Colab (for training)
- Polylactic Acid 1.5in cube
- Thermoplastic Urethane 1.5in cube

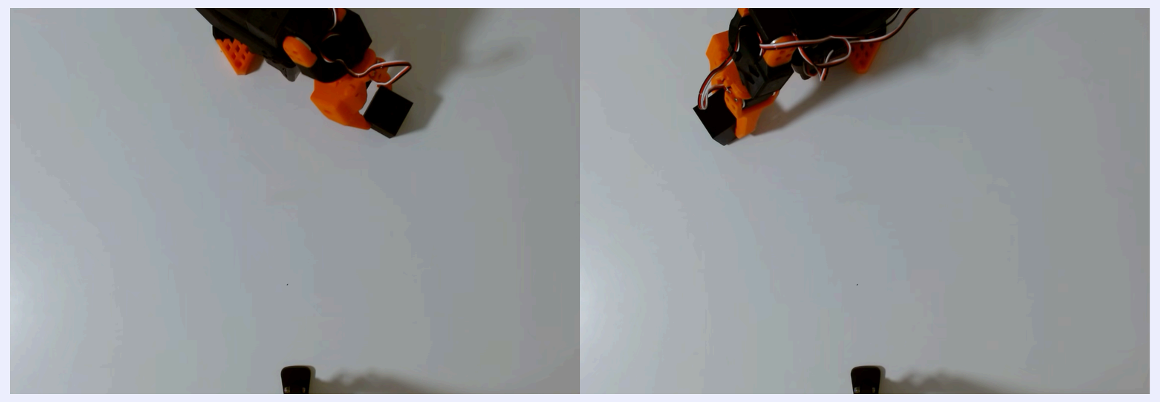

Figure 3: Left and right placement of soft vs. hard cubes

Data Collection

Training data was collected via teleoperation using two SO-101 arms in a leader-follower configuration. During 15-second pick-and-place tasks, webcam images, 6-DOF joint positions, and gripper motor currents were recorded at 30 Hz. PLA and TPU cubes were alternated at a fixed starting position. 56 recordings were used to train the model.

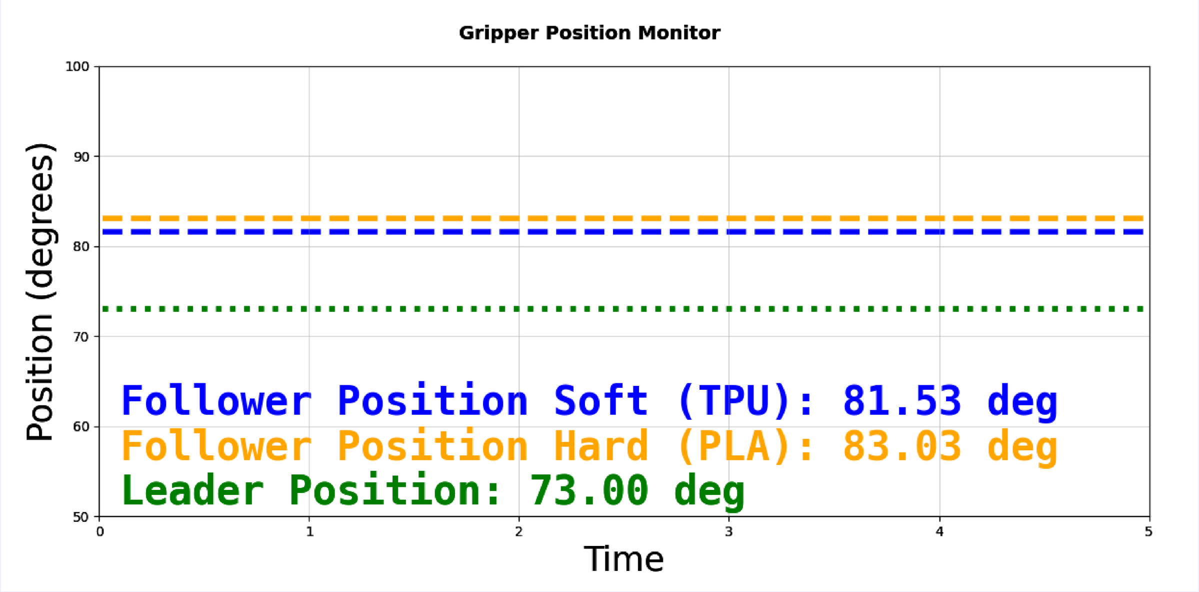

Figure 4: Comparison of follower motor positions for both TPU and PLA cubes and leader motor position.

Action Chunking Transformer (ACT)

Developed by Zhao et al. (2023), the Action Chunking Transformer (ACT) is an imitation learning architecture that predicts action sequences rather than single steps to minimize compounding errors. It utilizes a transformer-based policy to map camera images and joint positions to target commands. In this specific iteration, the model is augmented by appending gripper motor current to the joint position input.

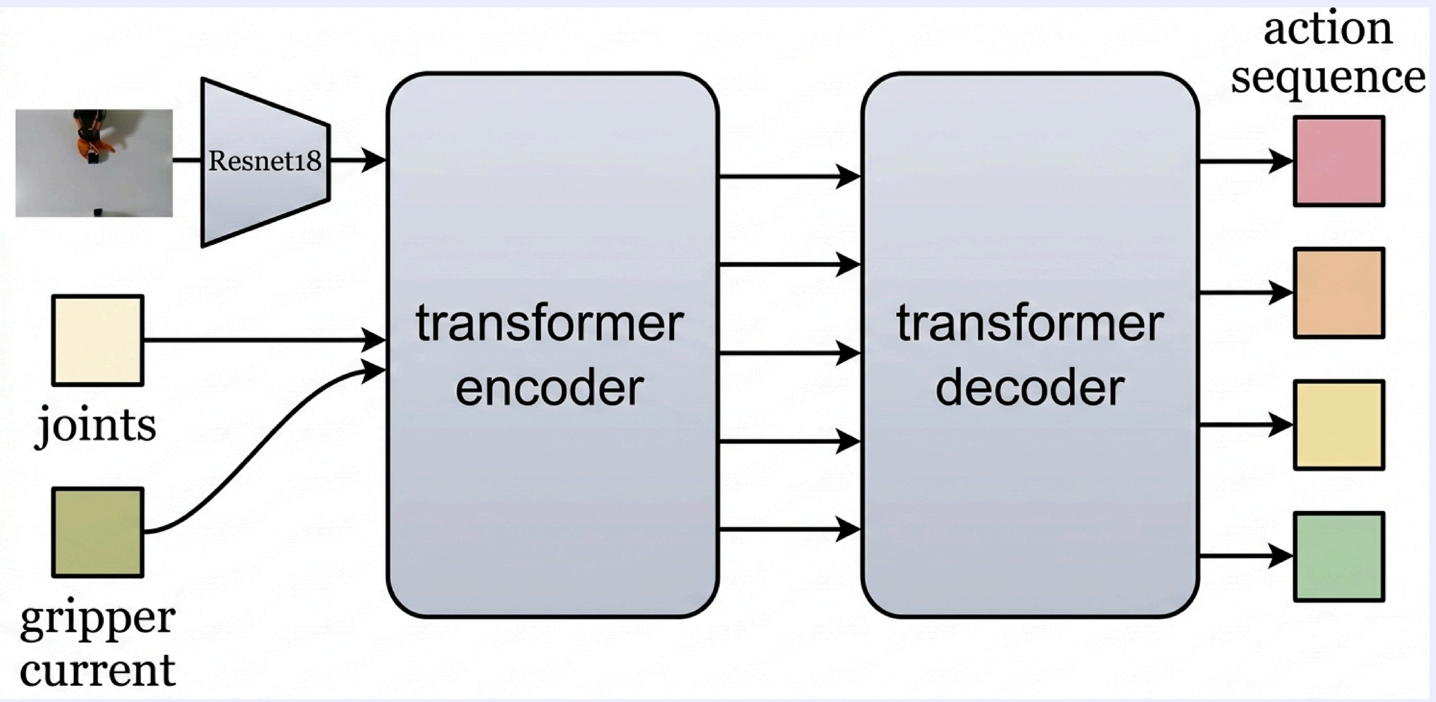

Figure 2: Model architecture: the gripper current feedback is an additional input to the transformer encoder, along with the image from the overhead camera and the joints states.

Training

Both models were trained in Google Colab, taking ~7 hours on a NVIDIA A100 GPU per model. To establish a baseline, the current-augmented dataset was modified by replacing all motor current values with zeros, effectively neutralizing that input.

Inference

During inference, the model generates a sequence of 100 action steps every 100 timesteps, executing each block in its entirety before the subsequent cycle. The generation of each 100-step chunk requires an average of 0.176 seconds. Execution of the chunk took 3.33 seconds in my 30Hz setup.

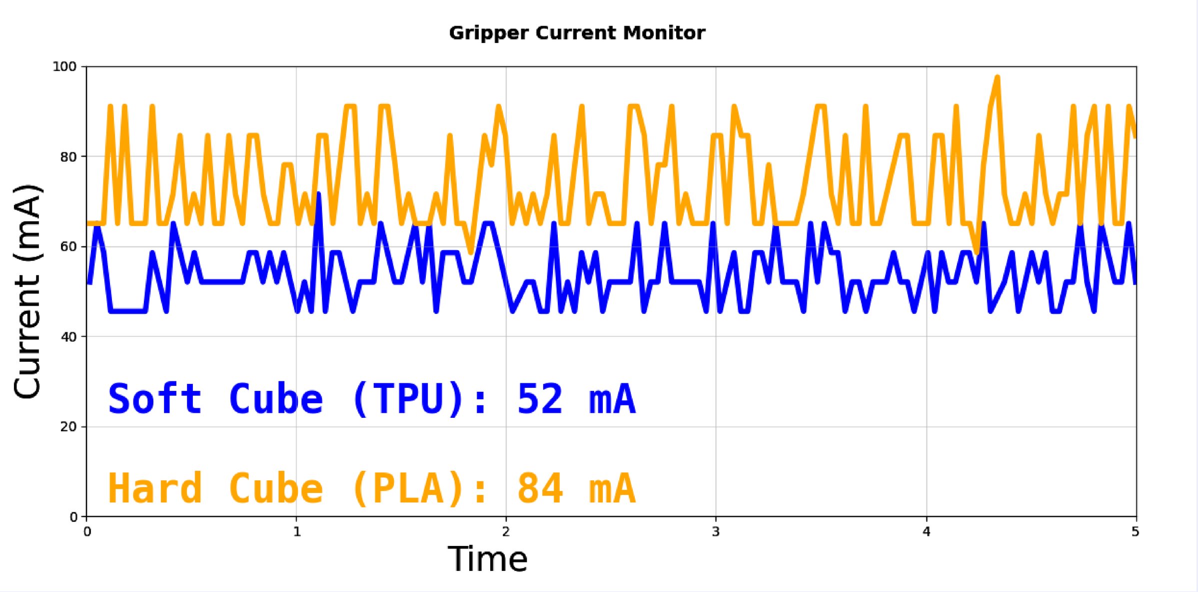

Figure 5: Comparison of raw gripper current feedback between the TPU and PLA cubes.

Results

Baseline ACT Model				Augmented Model			
TPU		PLA		TPU		PLA	
Success	Failure	Success	Failure	Success	Failure	Success	Failure
15	5	16	4	20	0	19	1
Accuracy: 77.5%				Accuracy: 95%			

Conclusions

This experiment tested whether motor current can provide a sense of touch in a low-cost robotic arm. The results supported the hypothesis. The baseline policy, using only joint positions and camera images, achieved 77.5% accuracy. When motor current feedback was incorporated, accuracy increased to 95%, as the policy learned to associate higher gripper motor currents with harder objects.

Although subtle differences in joint positions provide a discriminative signal, their small magnitude (1.44°) makes them susceptible to being treated as noise. Motor current offered a complementary and more reliable contact signal, allowing the model to confidently distinguish visually identical soft and hard objects.

These results demonstrate that low-cost motor current feedback provides complementary contact information, offering a pathway toward enhancing dexterity in affordable robotic systems.

Further Research

Future experiments could introduce visually distinct objects to test whether motor current feedback remains beneficial when visual cues are also available. Expanding current feedback to all six joints could provide richer contact information throughout the entire motion, potentially improving performance on more complex manipulation tasks. Further experiments can also explore more practical tasks, such as picking ripe fruits.