Actuator Network for Low cost and High safety

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Abstract—**In this study, we explore the performance of an actuator network that does not rely on torque sensors and propose a future actuator network designed to reduce vulnerabilities in untrained data while also eliminating the dependence on torque sensors. Our actuator network utilizes estimated torques instead of measured torques from sensors. Additionally, to mitigate the lack of training data, we performed data augmentation through modeling and collected data from various environments.**

I. Introduction

With the increasing research on learning-based controllers for robot control, the significance of sim-to-real has become more prominent [1], [2]. However, sim-to-real gap remains a major challenge that needs to be addressed. To tackle this issue, several approaches have been proposed, including: domain randomization [3]–[5], hierarchical control framework with model-based controllers [6]–[9], and system identification [1].

In particular, data-driven actuator network [1], [5] is gaining attention for achieving system identification in difficult-to-model systems. However, traditional actuator networks require torque sensors and face out-of-distribution (OOD) issues [10] when operating in regions with limited training data, such as near torque and velocity limits or in areas where actions change rapidly. As the degrees of freedom in a robot increase, the need for 1-axis torque sensors in each joint significantly raises costs, and collecting all the necessary data to address OOD issues becomes prohibitively expensive. To address this, we propose an actuator model that reduces costs and ensures safety.

II. Methods

In this section, we propose the design of an actuator network for low cost and high safety. For this, we focused on answering the following questions:

- Can we utilize the actuator model without a torque sensor? Moreover, how significant is the performance difference with and without a torque sensor?
- (future work) How does the learned model differ based on the data collection frequency (high frequency vs. low frequency)?
- (future work) For the safe operation of the robot, what efficient methods can solve the OOD problem when limited learning data is available?

To develop an actuator network that satisfies the above conditions, we propose two methods: utilizing torque estimation and data augmentation. For torque estimation, instead of using torque sensors as in conventional actuator models, we replace the sensor-measured values with torque estimates based on current values. The estimated torque is derived from the motor current, torque constant, and gear ratio as follows:

$$\tau_{est} = i * K_\tau * n, \tag{1}$$

where τ_{est} represents the estimated torque value, i denotes the current, K_τ is the torque constant, and n is the gear ratio.

To address the OOD problem, we use data augmentation based on DC motor modeling within a physically appropriate range. [11] We enriched the training dataset with data generated through modeling that leverages the relationship between angular velocity and torque of the motor.

The structure of the actuator network for training follows previous work [1] with minor modifications. The training data was collected from a real robot at 1kHz. Since this network is specifically designed for wheel joints, we used joint velocity error instead of joint position error in the loss function. The input layer includes both the joint velocity error and joint velocity from the current time step as well as from n-step previous time steps. Additionally, we collected the actuator network's training dataset by running a robot controller without the actuator network, under various conditions (e.g., load, slope, disturbance). This allowed the robot to operate at different speeds and learn a broad range of velocity-torque relationships.

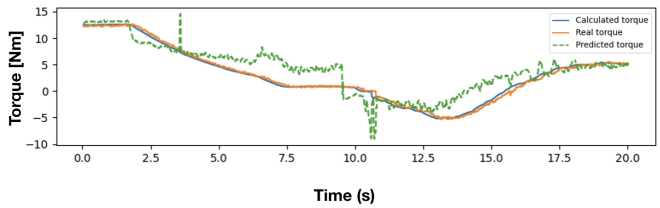

Fig. 1. Estimated target torque from the proposed actuator model

III. Results and Discussions

The experimental results showed that the network trained with estimated torque effectively tracked trends, despite some outliers. These outliers appeared more often in unfamiliar conditions, such as altered data input intervals or limited training data, requiring further analysis. The proposed actuator network captures internal joint stiffness, enabling more sensitive error responses. As the network considers input history, future work will focus on investigating its ability to identify non-Markovian properties and implementing it on a real robot.

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