Actuator Network for Low cost and High Safety

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Research Goal

The primary goal of this work is <u>to strengthen sim-to-real robustness using an actuator model without torque sensors, considering the issue of insufficient data.</u> In this study, we :

- Compare target torque mapping capabilities across different data frequencies.
- Analyze the model training with augmented data.

Methods

- **Train the network without using torque sensors**

The conventional actuator network [1] uses the actual torque (from the torque sensor) as the ground truth for training the model, but we replace it with torque estimates based on current values:

$$\tau_{est} = i * K_t * n$$

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

- **Use augmented, realistic data based on DC motor dynamics to train the network**

We select several data points that satisfy the relationship angular velocity and torque of the motor [2], and then perform linear interpolation with the existing data to generate training data.

$$V_a = \frac{R}{K_t}\tau + \frac{1}{K_v}\omega$$

V_a is the voltage applied to counteract the motor's resistance R, K_t is the torque constant, K_v is the speed constant, ω is the angular velocity.

The structure of the actuator network for training follows previous work [1] with minor modifications.

Actuator Network Description	
Input layer	6
Hidden layer	[32 32]
Output layer	1
Network Input	$\dot{q}_{t\sim t-2}$, $\dot{q}_{error\,t\sim t-2}$
Network Output	τ_d
Training data	$\dot{q}, \dot{q}_d, \tau_{est}$
Activation function	$softsign$
Loss function	$MSE(\tilde{\tau}_d, \tau_{est})$

- $\dot{q}$: Measured joint velocity
- $\dot{q}_d$: Desired joint velocity
- $\dot{q}_{error_t}$: $\dot{q}_d$ - $\dot{q}_t$
- $t\sim t-2$: History of the current state to two steps in the past
- τ_d : Actuator model predicted torque
- τ_{est} : Estimated torque based on current values

- Collected the training dataset by running a real robot controller (1000Hz) without the actuator network, under various conditions (e.g., load, slope, disturbance).
- 80% of the collected data is used for training, while 20% is allocated to the validation set.

Results

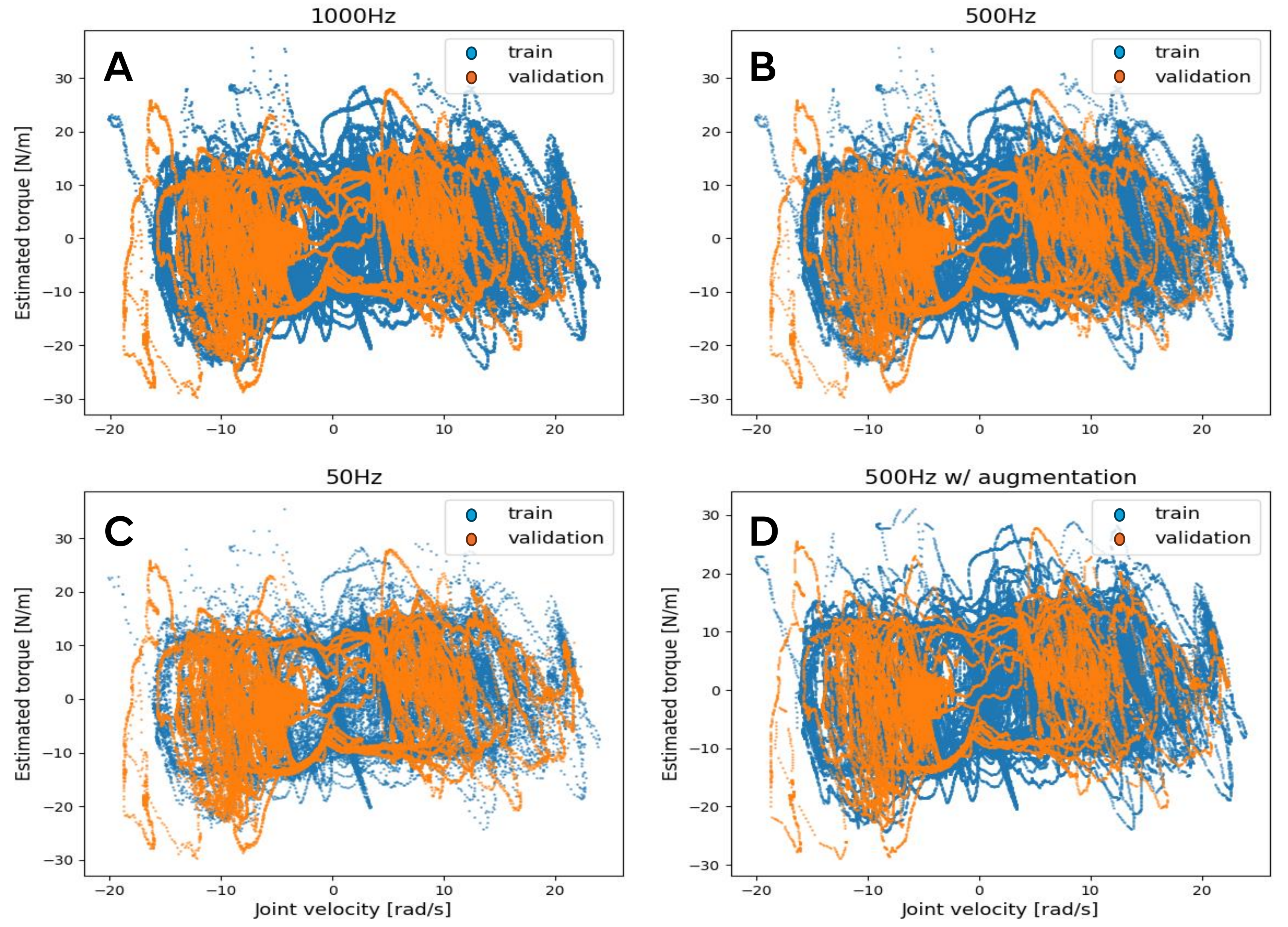

Fig 1. Train and validation data set (velocity and torque distribution). A is collected at 1000Hz, while B, C, D are resampled from A at 500Hz, 50Hz, and with data augmentation, respectively.

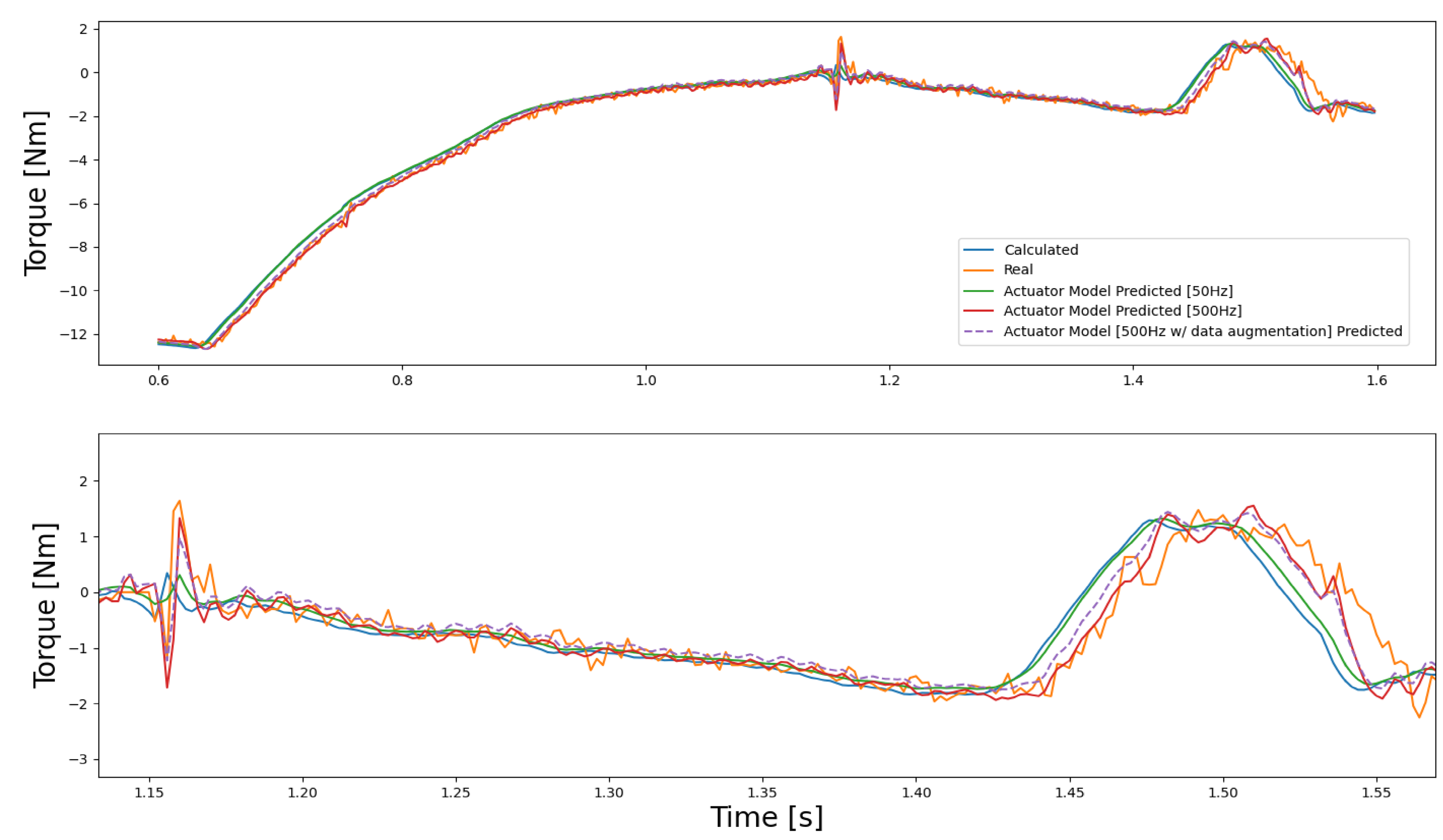

Fig 2. Estimation results of target torque. The calculated torque (blue) is computed from the robot controller.

- The trained model effectively maps joint states to joint torque even when trained with estimated torque and augmented data.
- Actuator network captures internal joint stiffness, enabling more sensitive error responses.
- A higher data sampling rate results in smaller errors compared to the idealized torque, but a lower rate provides smoother results.

Conclusion

- The proposed actuator network <u>predicts the target torque without a torque sensor (reducing costs)</u> and <u>shows potential for modeling unseen states (enhancing safety)</u> using data augmentation.
- Future work will explore the network's ability to identify non-Markovian properties.

References

[1] Jemin Hwangbo, Joonho Lee, Alexey Dosovitskiy, Dario Bellicoso, Vassilios Tsounis, Vladlen Koltun, and Marco Hutter. Learning agile and dynamic motor skills for legged robots. Science Robotics, 4(26):eaau5872, 2019.
[2] Young-Ha Shin, Tae-Gyu Song, Gwanghyeon Ji, and Hae-Won Park. Actuator-constrained reinforcement learning for high-speed quadrupedal locomotion. arXiv preprint arXiv:2312.17507, 2023.