University of Toronto Institute for Aerospace Studies / Dynamic Systems Lab

Knowledge Transfer Between Robots with Online Learning for Enhancing Robot Performance in Impromptu Trajectory Tracking

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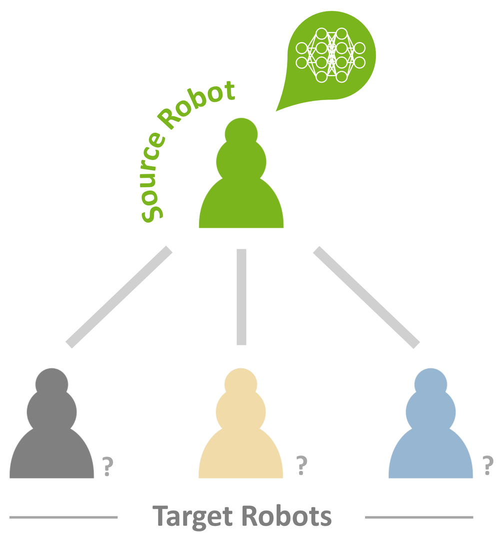
Introduction

Background

- Inverse dynamics models can be used to realize a desired robot motion or enhance a robot's performance.
- In [1] and [2], we used deep neural networks (DNNs) for learning inverse dynamics to enhance the tracking of a single robot.
- We observed approximately **50%-60% performance improvements** on 30 arbitrary hand-drawn test trajectories.

Research Questions

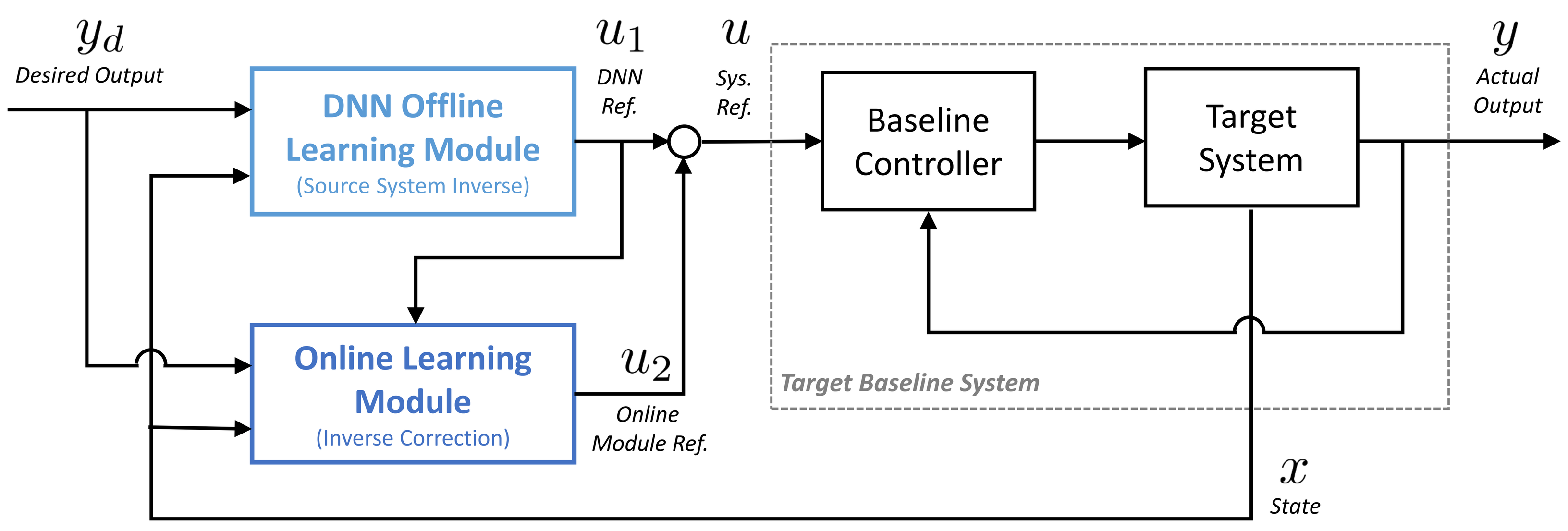
- If we have a DNN inverse module trained on one robot, can we **transfer the learned model** to enhance other robots in a team?
- How do we **characterize similarity** between robots, and what is the implication of having similar robots in the transfer problem?



Knowledge Transfer with Online Learning

Idea

- Learn an **online module** for transferring the **DNN inverse module** trained on a source robot to enhance a target robot



Black-Box Baseline Systems

- Consider source and target robot systems represented by

$$x(k+1) = f(x(k)) + g(x(k))\, u(k)$$
$$y(k) = h(x(k))$$

State
Actual Output
Reference Signal

- Assume *(i)* stable inverse dynamics (minimum phase) and *(ii)* well-defined and the same relative degree r
- Define $\mathcal{F}(x) = h\left(f^r(x)\right)$ and $\mathcal{G}(x) = \frac{\partial}{\partial u} h\left(f^{r-1}(f(x) + g(x)u)\right)$

Learning Modules

- The offline learning module (DNN) approximates the inverse of the source robot system and is previously trained on a rich dataset:

$$u_1(k) = \left(\mathcal{G}_s(x(k))\right)^{-1} \left(y_d(k+r) - \mathcal{F}_s(x(k))\right)$$

- The online learning module provides finer adjustments to the reference signal sent to the target robot system based on online data:

$$u_2(k) = \alpha\, e_p(k+r)$$

Adaptation Gain
Error Prediction

Similarity

Similarity Characterization

- Based on the state-to-output gain $\mathcal{A}$ and input-to-output gain $\mathcal{B}$ of the systems, we propose a measure to characterize the **dynamic similarity between the source and target robots**:

Similarity Measure →
$$S = \left[1 - \frac{\mathcal{B}_t}{\mathcal{B}_s} \quad \mathcal{A}_t - \frac{\mathcal{B}_t}{\mathcal{B}_s}\mathcal{A}_s\right]$$

Stability

- **Target robot system stability condition** under online learning uncertainties (see [3] for a proof):

$$|\alpha|\left(||S_2|| + \beta_2\right) < \beta_4 / L_1$$

Experimental Results

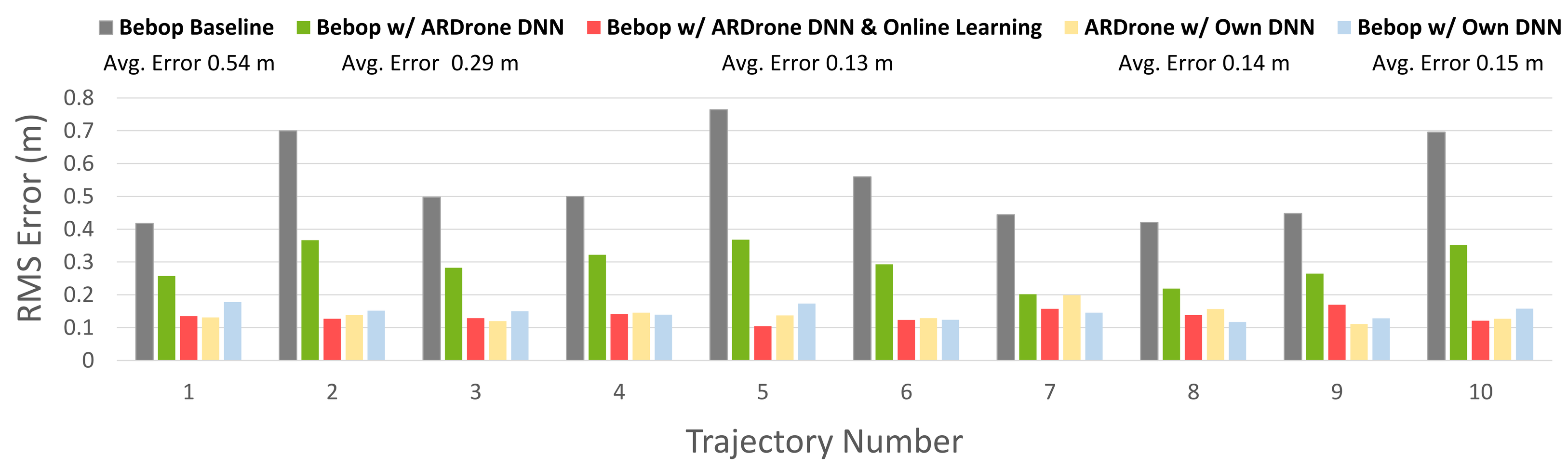
Fly as You Draw Experiments

- Quadrotors are expected to fly arbitrary trajectories generated from hand drawings accurately in the first attempts.

Sample Test Trajectories

Knowledge Transfer Results

- Platforms: Parrot ARDrone (source) and Parrot Bebop (target)



- On average over ten test trajectories, **the tracking error of the target quadrotor is reduced by 74%**.
- With **online learning**, overall target quadrotor performance is comparable to the cases where the source and the target quadrotors are enhanced by their own **DNN inverse modules**.

More Information

[1] Q. Li, J. Qian, Z. Zhu, X. Bao, M. K. Helwa and A. P. Schoellig, "Deep Neural Networks for Improved, Impromptu Trajectory Tracking of Quadrotors," International Conference on Robotics and Automation (ICRA) 2017. *Implementation of a fly-as-you-draw application.*

[2] S. Zhou, M. K. Helwa and A. P. Schoellig, "Design of Deep Neural Networks as Add-on Blocks for Improving Impromptu Trajectory Tracking," Conference on Decision and Control (CDC) 2017. *Guidelines for DNN module design – a general framework from control theory.*

[3] S. Zhou, A. Sarabakha, E. Kayacan, M. K. Helwa and A. P. Schoellig, "Knowledge Transfer Between Robots with Similar Dynamics for High-Accuracy Impromptu Trajectory Tracking," European Control Conference (ECC) 2019. *Transferring DNN inverse module across robots.*