Karlsruhe Institute of Technology

Intuitive Robots Lab (IRL)

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## Project Type

- ☐ Master Thesis
- ☑ Bachelor Thesis
- ☐ Research Project

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## Difficulty

Algorithmic

Math

Application

# Hybrid Models for Inverse Dynamics Modeling

## Description

The identification of a precise inverse dynamics model of an industrial robot is a key research area in robotics. By using a precise inverse model of the robot dynamics the reliance on feedback controllers for tracking accuracy can be reduced. This allows for precise and compliant motion, which is crucial for many real-world applications such as assembly tasks and human-robot interactions.

In this context hybrid models offer great potential [1]. They combine a traditional rigid-body dynamics model (RBD) with an additional neural network (NN). The RBD model predicts inertia forces, while the neural network can capture hard to model effects such as stick-slip and joint flexibilities from data. Combining the generalization of rigid-body dynamics models with additional data-driven terms to further optimize task-specific accuracy makes residual hybrid models ideal for compliant and precise motion tracking [2].

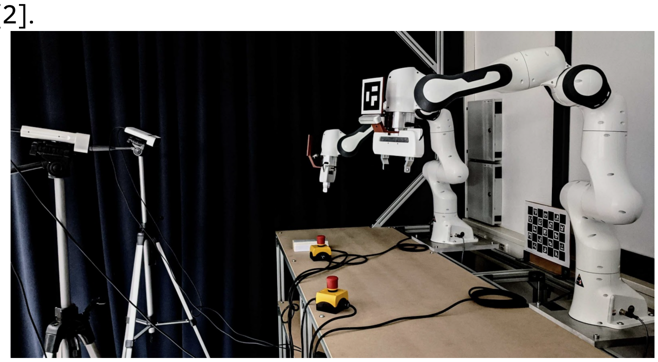

Figure 1: Robot hardware setup to test the trained models

The goal of the thesis is to explore hybrid models for learning the inverse dynamics on our real robot setup. We want to train and implement such hybrid models in our simulation and real robots. To test these models new motion tracking experiments must be designed and implemented. The goal is to run the trained models inside an inverse dynamics controller.

## Tasks

The tasks in this project will involve:

- Data collection: A new data set must be created to evaluate the the different inverse dynamics model. Data can be collected in our simulation framework and with the real robot by using generated trajectories and kinesthetic teaching.
- Implementation: Getting the new approach to work on our robot system and simulation framework for the hybrid models. We already have an working implementation of our model and training algorithms available.
- Model Training: After the data is collected and pre-processed the model and its loss function will be trained with the different datasets.
- Evaluation: The identified models of the robot will be evaluated in self-designed motion tracking experiments.

## References


[1] Michael Lutter and Jan Peters. Combining physics and deep learning to learn continuous-time dynamics models. *arXiv preprint arXiv:2110.01894*, 2021.

[2] Giovanni Sutanto, Austin Wang, Yixin Lin, Mustafa Mukadam, Gaurav Sukhatme, Akshara Rai, and Franziska Meier. Encoding physical constraints in differentiable newton-euler algorithm. In *Learning for Dynamics and Control*, pages 804–813. PMLR, 2020.