Exploration of Neural Network Architectures for Inertia Parameter Identification of a Robotic Arm

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Abstract. In this paper, we propose a machine learning based approach for identifying inertia parameters of robotic systems. The method is evaluated in simulation and compared against classical methods. Therefore, parameter identification based upon a numerical optimization is implemented and tested on ground truth data. For a case study, the physical simulation of a four degree of freedom robot arm is setup, formulating the problem with Newton-Euler equations in contrast to the conventional Lagrangian formulation. Additionally, a test methodology for assessing various neural network architectures is derived.

Keywords: Inertia parameters identification, robotics, numerical optimization, Newton-Euler, neural networks

1 Introduction

Inertia parameter identification is essential in robotics for precise motion planning and control [1]. The actual inertia parameters of robots can differ from those calculated from CAD drawings due to missing modeled parts, production tolerances, or modifications during production [2]. Various methods for inertia parameter identification have been proposed, as detailed by Leboutet et al. The most prevalent approach involves modeling the system, measuring the joint torques, and using motor encoder signals to derive the system's dynamic parameters at a specific time while driving it along an excitation trajectory [3].

Traditionally, the equations of motion (EoM) are derived from the Lagrangian formulation, which provides linear equations in the dynamic parameters at the joint level. This approach relies on motor encoder signals for the dynamic parameters, making it prone to noise and numerical differentiation errors when deriving the joint velocities and accelerations. Furthermore, the conventional approach uses the momentary torque values of the joint motors, often relying on indirect measurements of the torque-values through electrical current and voltage. Since the torque values are not directly measured on the mechanical side, nonlinear friction terms and other effects like thermal losses and electromagnetic influences are difficult to account for, reducing the applicability of these measurements in real-life settings [1].

In contrast, our approach uses Newton-Euler equations in an inertial frame, leveraging direct measurements of angular velocities and accelerations with a newly developed sensor concept at Offenburg University, along with an external force-torque measurement unit mounted between the robot and the fixture to measure the total resulting forces and moments produced by the movement of the system [4], [5]. This approach produces a set of six equations for any given point in time, compared to the n-equations produced by the EoM at the joint level, where n equals the number of joints of the studied robot.

2 Methodology

Our contribution is divided into two distinct solutions: First, classical numerical optimization, and second, the exploration and development of a machine learning approach using neural networks. Both methods are evaluated on a synthetic ground-truth dataset. The dataset includes inertia parameters for various robotic configurations as well as dynamic states (excitation frames). We simulate the corresponding reaction forces and moments, resulting from the dynamic movement of the particular robot configuration, computed via the Newton-Euler equations.

Numerical optimization is performed using solvers for both nonlinear and linearized problems. The results of this optimization serve as preliminary benchmarks for the artificial intelligence (AI) methods. The AI approach employs various fully connected feedforward network architectures, which are systematically tested in different configurations. Additionally, a more sophisticated AI approach was developed using Siamese network architectures and a custom loss function that incorporates physics constraints derived from the system's analytical equations. For all neural networks, extensive hyperparameter tuning was conducted based on common performance metrics and the visual inspection of learning behavior.

3 Data Generation

The Newton-Euler equations for all systems are formulated as symbolic equations corresponding software frameworks. As evaluation example, we simulate a four segment robotic arm, with multiple configurations and dynamic states. Each configuration is paired with corresponding forces and moments derived from the system equations. This approach avoids the pitfalls of trajectory-based methods, such as numerical differentiation and excitation trajectory optimization. The generated data includes the measurements of angular positions, velocities, and accelerations. The generated inertia parameters are additionally checked against boundary constraints to ensure validity in comparison to real-life robots.

4 Results

The results of the classical optimization provide a baseline for evaluating the AI models. The iterative exploration of neural network architectures revealed varying degrees of effectiveness. Networks were trained using different scaling methods and activation functions, with performance assessed through training loss and prediction accuracy. Despite extensive testing, AI based methods are still struggling to achieve the precision of classical numerical optimization without employing an enormous amount of data, parameters or computational power.

5 Conclusions

Our findings underscore the potential of combining direct dynamic measurements with advanced optimization and machine learning methods for inertia parameter identification. The performance of AI methods in comparison to numerical solvers suggests further research directions for future problems, e.g. the integration of physics-informed neural networks to combine the numerical efficiency and accuracy with data driven generalization capabilities.

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