MASTER THESIS

Thesis submitted in fulfillment of the requirements for the degree of Master of Science in Engineering at the University of Applied Sciences Technikum Wien - Degree Program Robotics Engineering

Alogrithmic Payload Estimation

By: Moritz Dönges, BSc

Student Number: 2310331024

Supervisor: Michael Schebeck, MSc

Vienna, November 22, 2025

Declaration

“As author and creator of this work to hand, I confirm with my signature knowledge of the relevant copyright regulations governed by higher education acts (see Urheberrechtsgesetz /Austrian copyright law as amended as well as the Statute on Studies Act Provisions / Examination Regulations of the UAS Technikum Wien as amended).

I hereby declare that I completed the present work independently and that any ideas, whether written by others or by myself, have been fully sourced and referenced. I am aware of any consequences I may face on the part of the degree program director if there should be evidence of missing autonomy and independence or evidence of any intent to fraudulently achieve a pass mark for this work (see Statute on Studies Act Provisions / Examination Regulations of the UAS Technikum Wien as amended).

I further declare that up to this date I have not published the work to hand nor have I presented it to another examination board in the same or similar form. I affirm that the version submitted matches the version in the upload tool.“

Vienna, November 22, 2025 Signature

Kurzfassung

Im Kontext der digitalen Fabrik an der UAS Technikum Wien, wo Menschen und Roboter sich die Aufgaben und den Arbeitsbereich teilen, ist die sichere und effiziente Handhabung von Nutzlasten von entscheidender Bedeutung. In der digitalen Fabrik der UAS werden Nutzlasten derzeit noch ohne Kenntnis ihrer internen Parameter gehandhabt, was zu potenziellen Manipulationsfehlern führen kann, die Menschen Schaden zufügen. Diese Studie beschreibt die Entwicklung einer fortschrittlichen Methode zur Kraft-/Drehmomentabschätzung, um die Fähigkeit eines UR5-Roboters zu verbessern, verschiedene Nutzlastbedingungen zu erkennen und zu handhaben. Diese Fähigkeit gewährleistet die Wahrnehmung des auf einer mobilen Industrieroboterplattform montierten UR5-Roboters, um den sicheren und effizienten Transfer von Nutzlasten zwischen verschiedenen Arbeitsbereichen innerhalb der Fabrik zu erleichtern. Die modernsten Methoden zur Kraft-/Drehmomentabschätzung für Industrieroboter nutzen neuronale Netze und Gauß-Prozesse als führende Methoden für genaue Nutzlastabschätzungen. Es wurde ein Gauß-Prozess-Modell entwickelt, um die Kräfte und Drehmomente abzuschätzen, die vom Roboter bei der Ausführung von Trajektorien erzeugt werden. In einem zukünftigen Projekt kann das Bewusstsein für Nutzlasten auf dem UR5-Roboter hinzugefügt werden. Auf diese Weise zielt die Studie darauf ab, die Intelligenz von Robotersystemen in industriellen Umgebungen zu verbessern und den Weg für eine höhere Produktivität und Sicherheit in digitalen Fertigungsumgebungen zu ebnen. Dieses Projekt führte auch zu einer Simulation, die eine Grundlage für die Aufzeichnung der Sensordaten aus dem UR5-Interieur.

Schlagworte: Gaussian Process, Force Estimation, Newton/Euler, UR5 Robot, Rigid Body

Abstract

In the context of the digital factory, at UAS Technikum Vienna, where humans and robots share the tasks and the workspace, the safe and efficient handling of payloads is essential. At the UAS digital factory payload is still handled without recognising anything about the payloads internal parameters, leading to potential manipulation failures causing human harm. This study describes the development of an advanced force/torque estimation method to improve a UR5 robots ability to recognize and handle different payload conditions. This capability ensures the perception of the UR5 robot mounted on a mobile industrial robot platform to facilitate the safe and efficient transfer of payloads between different workspaces within the factory. The state of the art methods of force/torque estimation for industrial robots serve neuronal networks and gaussian processes as the leading methods for accurate payload estimations. A gaussian process model has been developed to estimate the forces and torques generated by the robot when executing trajectories. In a future project face, an awareness of payloads can be added on the UR5 robot. In this way, the study aims to improve the intelligence of robotic systems in industrial environments and pave the way for higher productivity and safety in digital manufacturing environments. This project face also yeelted in a simulation that provides a basis to record the sensor data from the UR5's internal sensors and a force/torque sensor and a pipeline to train and evaluate gaussian process models.

Keywords: Gaussian Process, Force Estimation, Newton/Euler, UR5 Robot, Rigid Body

Acknowledgements

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

Contents

1 Introduction

1.1 Motivation

1.1.1 Context

As the robotics industry grows year over year, so does the number of robots operating around the world. It is estimated that there were approximately 3.4 million industrial robots in use worldwide in 2023 [1]. At the same time, the number of newly installed industrial robots has been increasing steadily since 2014; between 2021 and 2024, around 541 000 new industrial robots were installed per year [2]. Within this landscape, collaborative robots (cobots) represent about 10.5% of the industrial robot market, with 57 040 new units deployed in 2023, and annual cobot installations since 2020, 2022, and 2023 reaching roughly 50 000 units per year; importantly, these cobots are expected to complement rather than replace traditional industrial robots [3].

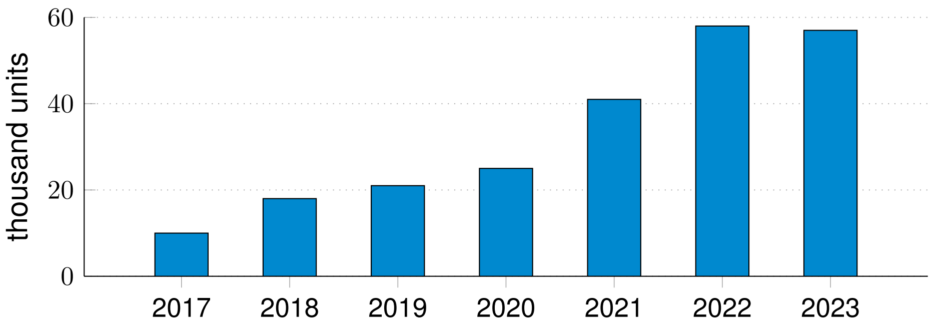

Figure 1: Global annual installations of collaborative robots from 2017 to 2023 (in thousand units). Data from [3].

The growing deployment of, and increasing collaboration with, robots imposes stringent requirements on safety and performance. As tasks become more complex and humans and robots share workspaces more closely, two closely related problems become central: safe manipulation of payloads and safe physical human-robot interaction. Addressing both problems requires accurate knowledge of the inertial parameters of the manipulated object together with consistent estimation of the robot's dynamic state and interaction forces. A collaborative robot must therefore maintain an internal representation of the mass-inertia properties of the payload or tool it manipulates and of the forces exchanged with its environment. This dynamic awareness is a prerequisite for compliant, contact-rich behaviour and for precise, high-performance manipulation in close proximity to humans. HERE NEED TO ADD THE CITES, first sort from old Libaray. (Motivation.md)

2 State of the Art

2.1 Research Strategy

- $C_1 =$ Classical / Observers
- $C_2 =$ Gaussian Process (GP)
- $C_3 =$ Deep Sequence Models (MLP / GRU / TCN / Transformer / LSTM)
- $C_4 =$ Physics-Informed / Differentiable
- $C_5 =$ Surveys
- $C_T =$ Goal & Domain Terms
  - $C_{mt} =$ Estimation & Modeling Terms
  - $C_{ct} =$ Robotics Context Terms

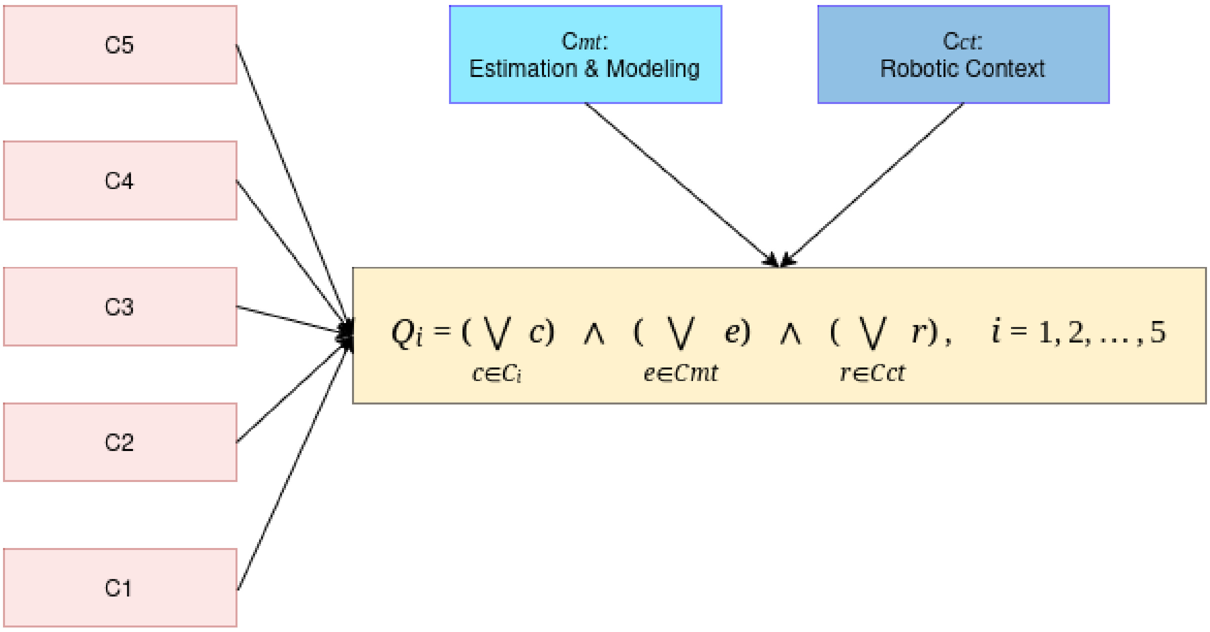

Figure 2: Query logic used to categorise the SoA papers. Each category Q_i is formed by combining content clusters C_i with estimation & modelling terms C_{mt} and robotics context terms C_{ct}. The combined representation C and query set Q are formed by the union of their respective subsets.

Here is written that the terms of the categories are found in the appendix and why and how this Strategy is executed. Which then leads into the remaining 36 relevant SoA papers in this study.

Table 1: Overview of query results by category.

Query	Relev. SoA	Rigid-body	Payload	Both
$\mathbf{Q_1}$ = Classical / Observers	17	7	7	3
$\mathbf{Q_2}$ = Gaussian Process (GP)	4	4	0	0
$\mathbf{Q_3}$ = Deep Sequence Models	8	4	4	0
$\mathbf{Q_4}$ = Physics-Informed / Diff.	5	5	0	0
$\mathbf{Q_5}$ = Surveys	2	–	–	–
Total	**36**	**20**	**11**	**3**

2.2 One-page condensed SoA summary for Q1

Category Q1 groups classical **model-based methods for robot and payload dynamics and interaction force estimation**, mostly based on **linearly parameterised rigid-body dynamics (RBD) and LS/WLS regressors**, sometimes combined with observers and Kalman filters. Across the papers[4][5][6], **Least Squares (LS), Weighted LS (WLS) and LS-Newton-Euler (LS-NE) regressors** are the dominant tools for both **robot dynamic parameter identification (RDPI)** and **payload dynamic parameter identification (PDPI)**. They are used in joint space, in motor-current space and in sensor frames, and provide **strong performance for mass, centre of mass (CoM) and joint-torque prediction** when trajectories are sufficiently exciting.

A large subset of works demonstrates that **neither a nominal CAD-based RBD model nor an FT sensor is strictly necessary**.[7],[8],[9],[10],[4], Q1.5–Q1.8, Q1.13, Q1.15 and Q1.16 build the regressor directly from measured joint states and controller torques, sometimes in **fully decoupled formulations** or via **residual-torque decomposition**. They use **constant-velocity/acceleration S-curve trajectories, Fourier trajectories or repeated sections** to decorrelate parameters and improve conditioning. These approaches typically obtain **very good mass estimates and acceptable CoM**, with **inertia remaining the weakest part of the identification**, especially for short trajectories.

Several methods employ **two-stage pipelines**: static poses for mass and CoM, followed by dynamic trajectories for inertia (e.g. Q1.5 and Q1.7). Q1.7 also shows that such schemes scale to **heavy ($\sim 40\,\mathrm{kg}$) payloads**, and can feed into **contact force estimation and compensation** with moderate batch times ($\approx 10\,\mathrm{s}$ for contact, $\approx 40\,\mathrm{s}$ for payload).

Where an **NRB model is available or identified offline**, it is commonly combined with **observers** for external torque and force estimation. Q1.2 and Q1.3 use LS-NE-based torque prediction together with **momentum or sliding-mode observers** to estimate external joint torques and EE forces. Q1.4 and Q1.17 combine RBD with **(adaptive) Kalman filters / disturbance observers** and explicit friction models (Stribeck or NN-based). These approaches can yield **good EE force estimation and collision detection**, but they are sensitive to model mismatch and friction modelling; Q1.17 reports good behaviour without external forces but large errors (up to $\approx 9\,\mathrm{Nm}$) under contact. **Sensorless interaction-force estimation** is addressed in Q1.3, Q1.12 and Q1.17. Q1.12, for example, uses LS-NE identification of $M(q)$, $C(q)$ and $G(q)$, then runs a **High-Order Finite-Time Observer (HOFFTO)** in joint space, using an FT sensor only as ground truth. This yields **good joint-torque prediction and acceptable EE force estimates**, but still depends on accurate offline dynamics. Finally, Q1.14 shows that combining LS-NE predicted torques with measured joint torques enables **robust collision detection and localisation of the collided joint** using simple residual thresholds, again assuming a reasonably accurate NRB model.

In summary, **Q1 methods show that classical LS-type identification and observers are mature and effective**:

- **Mass and CoM** can be identified very reliably, even **without NRB and without FT sensors**.
- **Inertia** is consistently harder and requires **carefully designed dynamic excitation**, and still tends to be less accurate or weakly validated.
- **Torque prediction, contact detection and simple EE force estimation** are already at a high level with these methods, but they **rely on good friction modelling and reasonably accurate dynamics**.

Bibliography

[1] Stanford Institute for Human-Centered Artificial Intelligence (HAI). "Artificial intelligence index report 2025," Accessed: Nov. 22, 2025. [Online]. Available: https://hai.stanford.edu/ai-index/2025-ai-index-report

[2] International Federation of Robotics. "World robotics 2025 report." Press release, Sept. 25, 2025, Accessed: Nov. 22, 2025. [Online]. Available: https://ifr.org/ifr-press-releases/news/global-robot-demand-in-factories-doubles-over-10-years

[3] International Federation of Robotics. "Collaborative robots – how robots work alongside humans." Bar chart illustration, Accessed: Nov. 22, 2025. [Online]. Available: https://ifr.org/ifr-press-releases/news/how-robots-work-alongside-humans

[4] M. Liu et al., "A two-stage payload dynamic parameter identification method for interactive industrial robots with large components," IEEE Transactions on Automation Science and Engineering, vol. 22, pp. 13 871–13 883, 2025. DOI: 10.1109/TASE.2025.3557064

[5] T. Xu et al., "Identifying current dynamics of robot payload based on iterative weighting estimation," IEEE Transactions on Instrumentation and Measurement, vol. 74, pp. 1–14, 2025. DOI: 10.1109/TIM.2025.3554883

[6] T. Xu, J. Fan, Q. Fang, Y. Zhu, and J. Zhao, "An accurate identification method based on double weighting for inertial parameters of robot payloads," Robotica, vol. 40, pp. 1–17, 2022. DOI: 10.1017/S0263574722000960 [Online]. Available: https://doi.org/10.1017/S0263574722000960

[7] P. Nadeau, M. Giamou, and J. Kelly, "Fast object inertial parameter identification for collaborative robots," in 2022 International Conference on Robotics and Automation (ICRA), 2022, pp. 3560–3566. DOI: 10.1109/ICRA46639.2022.9916213

[8] M. Tang, Y. Yan, B. An, W. Wang, and Y. Zhang, "Dynamic parameter identification of collaborative robot based on wls-rwpso algorithm," Machines, vol. 11, no. 2, p. 316, 2023. DOI: 10.3390/machines11020316 [Online]. Available: https://www.mdpi.com/2075-1702/11/2/316

[9] S. Zhang, M. Yuan, Z. Huo, J. Huang, and X. Zhang, "Accurate payload dynamics estimation and compensation of a robotic manipulator without external motion measuring sensors," in 2025 11th International Conference on Electrical Engineering, Control and Robotics (EECR), 2025, pp. 1–8. DOI: 10.1109/EECR64516.2025.11077346

[10] J. Hu, Z. Chen, Y. Lin, Z. Chen, B. Yao, and X. Ma, "On the fully decoupled rigid-body dynamics identification of serial industrial robots," IEEE Transactions on Robotics, vol. 41, pp. 4588–4605, 2025. DOI: 10.1109/TRO.2025.3578229

List of Figures

List of Tables

List of source codes