Master's Department of Engineering Sciences

MSc in Automation Engineering and Robotics

Name of the unit: Estimation and Identification for Robotics and Dynamical Systems

Lecturer: Nazih MECHBAL (nazih.mechbal@ensam.eu)
Course code:
Student workload: 32 h of lectures, 12 h of tutorials, 12 h of labs
Credits: 6 ECTS
Specialization tracks: ☒ ROBOT ☐ SI ☐ MeDH
Semester offered: ☐ S1 ☐ S2 ☒ S3 ☐ S4
Language of instruction: ☐ French ☒ English
Targeted audience: ☐ Engineering Sciences students ☒ Other (specify): ENSAM
Localization : ☐ PMC Campus ☐ Other (specify): Campus ENSAM Paris

Course Overview

This course provides the fundamentals of estimation and parametric identification for dynamical systems based on experimentally measured data, with a strong focus on robotic applications (industrial robots, unmanned drone, ...). It covers the main methodologies for estimating the states of multi-physical systems and for identifying the physical parameters of robotic systems from input-output measurements. The course addresses key aspects such as signal processing, model design, and parameter estimation. Advanced state estimation techniques are studied, including the Kalman Filter and its nonlinear extensions: Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Particle Filter (PF), as well as modern learning-based approaches such as the Neural Kalman Filter (NKF). Joint state and parameter estimation methods are also introduced through augmented state formulations. The course reviews the fundamentals of signal processing for system identification (discrete-time analysis, digital filtering, spectral methods) and extends them toward nonlinear signal processing and data-driven approaches based on artificial intelligence. Finally, the course explores the specific problem of parameter identification for flexible robotic manipulators, with applications to robotic machining and real-world experimental systems. All methods are illustrated through practical implementation using dedicated software tools (MATLAB/Octave, Python), with an emphasis on real data and engineering applications.A strong emphasis is placed on implementation and on applications to real robotic systems.

Keywords: State estimation, parametric identification, Data-driven Modeling, recursive Bayesian estimation, Kalman Filters, Non linear estimations, Signal Processing, Robotic machining, Flexible robot manipulators,

Prerequisites

Students should have previously acquired the following prerequisites to follow this course:

- Linear algebra and basic control theory
- Continuous and discrete-time dynamical systems (state-space representation)
- Probability and random variables
- Signal processing fundamentals
- Solid mechanics and vibrations
- Basic programming skills (Matlab or Python)

Intended Learning Outcomes

By the end of this course, students will be able to:

1. Review probability theory and Bayesian inference.

2. Understand the main methods of linear estimation and give their properties.
3. Compute least squares and recursive least squares (RLS) estimates.
4. Design and implement Kalman Filter (KF) and steady-state KF (as a state observer) in Matlab/Octave.
5. Design and implement nonlinear Kalman filters (EKF, UKF).
6. Understand the recursive Bayesian estimation for nonlinear non-Gaussian systems
7. Design and implement a Particuke Filter in Matlab/Octave
8. Understand the neuronal Kalman filter (NKF)
9. Design the signal processing chain to acquire reliable data in a robotic context
10. Identify parametric models (ARX, ARMAX, etc.) from experimental data.
11. Apply data-driven and machine learning approaches for system identification in a robotic context
12. Carry out dynamical modelling of an industrial robot including flexibilities and identify its parameters ; Process digital experimental signals acquired on an actual industrial robot with flexibilities

Indicative Teaching Sequence and Methods

Week	C/TD/TP*	Content	Preparation	Learn. outc.
S1	C	Probability theory and Bayesian inference	Review probability basics	AAV1
S2	C+TD	Least squares, ML and MAP estimation	Exercises on estimation methods	AAV2, AAV3
S3	C+TD	Recursive estimation (RLS)	Implementation exercises	AAV3
S4	C+TD/TP Num	Kalman Filter (KF)	Matlab implementation of KF	AAV4
S5	C+TD/TP Num	Extended and Unscented Kalman Filters (EKF, UKF)	Nonlinear estimation exercises	AAV5, AAV6
S6	C+Exam	Particle Filters (short lecture) + Midterm written test	Revision	AAV1-AAV5
S7	C	Limitations of model-based estimation	Discussion and case studies	AAV6
S8	C	Neural Kalman Filter (NKF)	Introduction and implementation examples	AAV8
S9	C+TD/TP Num	Hybrid estimation (KF vs NKF)	Project-based work	AAV4
S10	C+TD/TP Num	Advanced Signal Processing for robotics	Signam Processing introcuction and implemantation	AAV4
S11	C+TD/TP Num	Parametric identification (ARX, ARMAX models, ...)	Model structure exercises	AAV9, AAV11
S12	C+TD/TP Num	Data-driven identification	Comparison with parametric models	AAV12
S13	Exam	Final written exam (estimation and identification)	Revision	AAV1-AAV12
S14	C	Modeling of flexible robotic manipulators	Review robot dynamics	AAV12
S15 and S16	TP/DM	Identification of flexible robotic manipulators	Experimental data analysis / Project-based work	AAV12

* C/TD/TP respectively corresponds to lectures, tutorials and lab sessions.

Indicative Assessment of Intended Learning Outcomes (1st session)

Week	Individ./group	In-person/remote	Type of exam	Evaluated outcomes	Scale %
S6	Individual	In-person	Midterm written test (estimation methods)	AAV1-AAV5	40 %
S12	Individual	In-person	Final written exam (estimation + identification)	AAV1-AAV12	30 %
S15	Group	In-person	Practical work / mini-project (robotic system identification and estimation)	AAV8-AAV15	30 %

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Session	Individ./group	In-person/remote	Type of exam	Evaluated outcomes	Scale %

Bibliographic references

- Lennart Ljung, System Identification: Theory for the User, 2nd ed. Prentice Hall, 1999.
- T. Kailath, A. Sayed, and B. Hassibi, Linear Estimation, Prentice Hall, 2000.
- G. Revach et al., KalmanNet: Neural Network Aided Kalman Filtering, 2021.
- R. Krishnan et al., Deep Kalman Filters, 2017.
- Oppenheim, Alan V., Ronald W. Schafer, and John R. Buck. Discrete-Time Signal Processing. 2nd ed. Upper Saddle River, N.J: Prentice Hall, 1999.

Date of generation of this unit description: October 6, 2026