le cnam cedric EA4629

M2 Internship Proposal (5–6 months, starting March 2026)

Hybrid Estimation Methods for Strongly Uncertain Nonlinear Systems

1 Context and Motivation

Autonomous nonlinear systems—such as ground and aerial vehicles, mobile robots, or cyber-physical systems—play an increasingly important role in emerging technologies. Their behavior results from complex interactions between mechanical and electronic dynamics, imperfect sensors, and perception or decision-making algorithms. Modeling such systems remains challenging due to strong nonlinearities, uncertainties, and unmodeled effects including friction, sensor drift, and delays [1].

Classical nonlinear observers allow the reconstruction of internal states from partial measurements, but they require sufficiently accurate models [2]. In contrast, *data-driven* and deep learning approaches show remarkable potential for capturing hard-to-model dynamics, but they generally lack theoretical guarantees in terms of stability and robustness [4].

This internship aims at developing a hybrid methodology that unifies model-based observers (affine observers, high-gain observers, Unknown Input Observers (UIOs), interval observers, etc.) with machine learning methods (generative models, latent-state networks, hybrid architectures) in order to provide robust, explainable, and uncertainty-quantified state estimation.

2 Objectives and Scientific Program of the Internship

The overall objective of this internship is to contribute to the development of a new generation of hybrid observers for uncertain nonlinear systems by combining physical modeling, robust estimation, and machine learning. The challenge is to propose a unified framework that reconciles theoretical guarantees (stability, error bounds) with the ability to capture complex and poorly modeled dynamics.

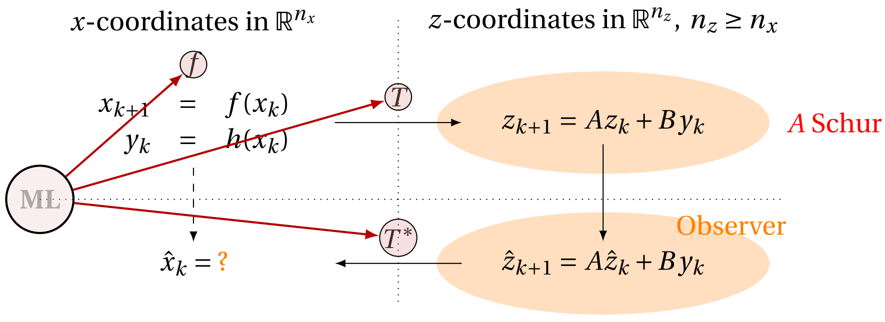

Figure 1: Conceptual diagram of a hybrid observer.

The internship is organized around the following complementary scientific axes.

1. Nonlinear Modeling and Data Generation (M1–M2)

A realistic 2D autonomous vehicle model will be developed, including nonlinearities, saturations, noise, and disturbances. Synthetic and simulated datasets will be generated for training, calibration, and validation of the observers.

2. Observability Analysis and Robust Observer Design (M2–M4)

A rigorous nonlinear observability analysis will be carried out [5, 3]. Based on this analysis, robust observers will be designed to ensure stability guarantees and explicit quantification of estimation error bounds.

3. Hybrid Observers Based on Analytical Models and AI (M4–M5)

Hybrid observers will be developed by combining:

- an analytical structure ensuring stability and robustness;
- a learned module (Recurrent Neural Networks (RNNs), generative models, latent-state networks) capable of compensating for residual unmodeled dynamics.

The seamless integration of observer theory and machine learning, as well as the interpretability of the AI modules, will constitute a central research axis.

4. Numerical Validation and Thesis Finalization (M5–M6)

The proposed methods will be validated on advanced simulators (OpenAI Gym, CARLA, MATLAB, and Python). The thesis will be written progressively as each research axis is completed, and will be intensively finalized and revised during the last month.

Expected areas of expertise:

Strong background and interest in the interaction between control theory, applied mathematics, and artificial intelligence. Programming skills in MATLAB and/or Python are required.

Application:

Curriculum vitae, motivation letter, and academic transcripts (M2 and, if applicable, previous degrees).

Supervision Team:

Main Supervisors/Contacts: Thach Ngoc Dinh, Associate Professor (ngoc-thach.dinh@lecnam.net) and Jae Yun Jun Kim, Associate Professor (jae-yun.jun-kim@ece.fr)

Collaborators: Mathieu Moze, Samia Bouzefrane, and Lyes Khoukhi

References

[1] Julian Berberich and Frank Allgöwer. "An Overview of Systems-Theoretic Guarantees in Data-Driven Model Predictive Control". In: *Annual Review of Control, Robotics, and Autonomous Systems* 8.1 (2025), pp. 77–100. DOI: 10.1146/annurev-control-030323-024328.

[2] P. Bernard. "Observer Design for Nonlinear Systems". In: *Lecture Notes in Control and Information Sciences* 479 (2019). DOI: https://doi.org/10.1007/978-3-030-11146-5.

[3] Pierre-Jean Bristeau, Nicolas Petit, and Laurent Praly. "Design of a navigation filter by analysis of local observability". In: *49th IEEE Conference on Decision and Control (CDC)*. 2010, pp. 1298–1305. DOI: 10.1109/CDC.2010.5717848.

[4] Charles Dawson, Sicun Gao, and Chuchu Fan. "Safe Control With Learned Certificates: A Survey of Neural Lyapunov, Barrier, and Contraction Methods for Robotics and Control". In: *IEEE Transactions on Robotics* 39.3 (2023), pp. 1749–1767. DOI: 10.1109/TRO.2022.3232542.

[5] G. Q. B. Tran and P. Bernard. "Arbitrarily Fast Robust KKL Observer for Nonlinear Time-Varying Discrete Systems". In: *IEEE Transactions on Automatic Control* 69.3 (2024), pp. 1520–1535. DOI: 10.1109/TAC.2023.3328833.