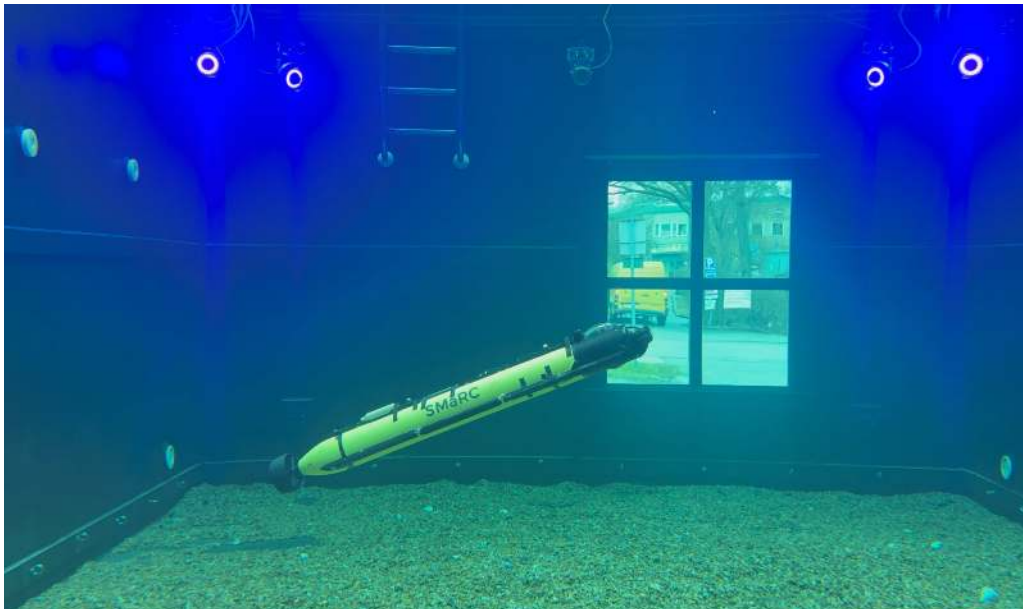
Active Learning for Model-Based Control of Autonomous Underwater Vehicles

Keywords: Autonomous Underwater Vehicles, Active Learning, Gaussian Processes, Model Predictive Control, Robotics

Accurate dynamic models are essential for the control of autonomous underwater vehicles (AUVs). However, complex hydrodynamic effects and uncertain parameters make these dynamics challenging to model. Gaussian Processes (GPs) offer a promising approach by learning the discrepancies between nominal models and actual vehicle behavior [1].



SAM inside the Marinarium.

At KTH, we have developed a Gaussian Process-based Model Predictive Control (GP-MPC) framework for nonholonomic AUVs. While this approach can improve control performance, its effectiveness depends on the quality of the training data. Currently, data collection relies on manually designed excitation trajectories, which may be inefficient or provide insufficient coverage of relevant operating conditions.

Active learning offers an alternative by enabling the vehicle to autonomously select informative maneuvers and systematically improve its learned dynamics model [2, 3].

The goal of this master's thesis is to **investigate and experimentally evaluate active learning strategies for improving the learned dynamics of nonholonomic AUVs**.

Building upon an existing GP-MPC framework and ongoing research on active learning, the student will investigate how an AUV can autonomously collect informative training data while respecting its motion constraints and the physical limitations of the experimental environment [4].

The proposed approach will be evaluated in simulation and **validated through experiments on a real AUV platform at KTH**, focusing on data efficiency, model prediction accuracy, and control performance.

The thesis will involve:

1. Literature review on active learning and learning-based control.
2. Familiarization with the existing GP-MPC framework.
3. Investigation and development of active learning strategies for constrained AUV operations.
4. Integration with the existing GP residual learning framework.
5. Simulation studies and experimental validation on a real AUV, including comparison with manually designed excitation trajectories.

The project is suitable for students with a background in Robotics, Automatic Control, Machine Learning, or related fields. Knowledge of control theory, optimization, and Python programming is expected. Experience with Gaussian Processes, MPC, ROS 2, or robotic hardware is advantageous.

References

[1] D. Dörner, G. Troni, I. Torroba, and I. Stenius, “Gaussian Process-Augmented Model Predictive Contouring Control for 6-DoF Trajectory Tracking with a Holonomic AUV,” Nov. 10, 2026, *arXiv*: arXiv:2611.14373. doi: 10.48550/arXiv.2611.14373.

[2] A. Capone et al., “Localized active learning of Gaussian process state space models,” *Learning for Dynamics and Control*, 2020. https://proceedings.mlr.press/v120/capone20a.html

[3] W. Zhang et al., “Active Model Learning using Informative Trajectories for Improved Closed-Loop Control on Real Robots,” 2021. https://arxiv.org/abs/2101.08100

[4] Y. Sui et al., “Safe Exploration for Optimization with Gaussian Processes,” *International Conference on Machine Learning*, 2015. https://proceedings.mlr.press/v37/sui15.html

Contact: David Dörner (KTH, ddorner@kth.se)