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Lifelong Learning for Vision based AUV Control.

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Lifelong Learning for Vision based AUV Control.

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Impact

Marine research, underwater structure maintenance and pipeline surveillance are frequent and expensive operations. Controlling autonomous underwater vehicles (AUVs) in this environment is challenging due to non-linear dynamics. We also consider the dynamics evolution that can rise from current, thruster decay, payload change etc. We search for a controller that can efficiently control AUV in non-linear and time-varying dynamics. This should lead to a controller that quickly adapts to changes in the AUV configuration allowing modification (new sensors, moving sensors around), and guarantees that the AUV should finish and return from every mission as long as there isn't a critical failure. This research should drastically reduce the cost of operating an AUV and the controller tuning time.

Objectives

The goal is to create an easy-to-use adaptive controller for non-linear environments.

- Implement a Model-Based Controller.
- Learn the dynamical model of the robot using prior data.
- Adapt the learned model to various incurring dynamics changes.
- Compare its raw performance against state-of-the-art controllers.
- Compare its performance under dynamics changes.
- Incorporate vision inside the controller through world-models (VAE, world model etc).

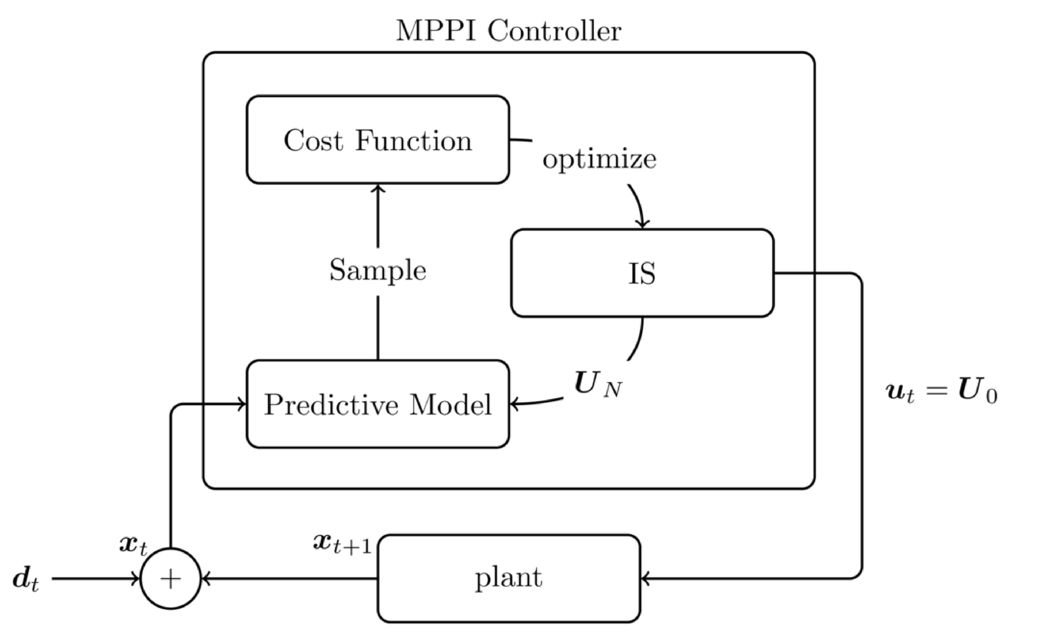
Methodology

To address the challenges, we use the following methods:

- *Controller:* The choice of the controller is based on Model Predictive Path Integral (MPPI) [1]. MPPI is a sampling-based controller working in the action space. Using a *non-linear* predictive model, the controller samples a set of actions and generates expected trajectories. It then assigns a weight to each sample with an objective-dependent cost function. The action decision is based on the weighted average contribution of each samples.
- *Predictive Model:* We decide to work with neural networks due to their ability to model any non-linear function, their inference time and the new popularity of adaptive methods (*sim2real*, *few-shot-learning*).

  We also use the analytical *Fossen* model [2] as ground truth to compare our NN-MPPI algortihm against. Those equation model the dynamics equation with ODEs. However, the parameters of the model are difficult and long to acquire.

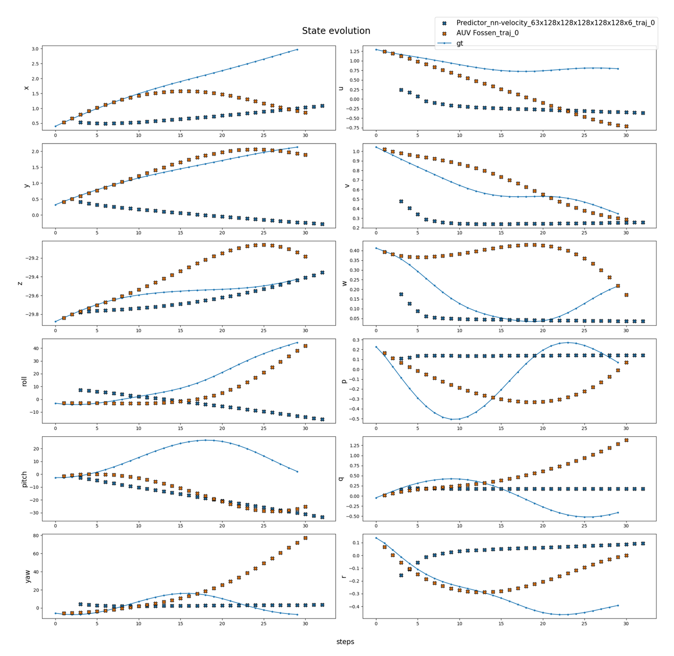
Architecture



Software architecture. The state is first propagated using randomly sampled actions with the *predictive model*. Each sampled is assigned a weights through the cost function. Finally the optimal action is computed using importance sampling.

Current results

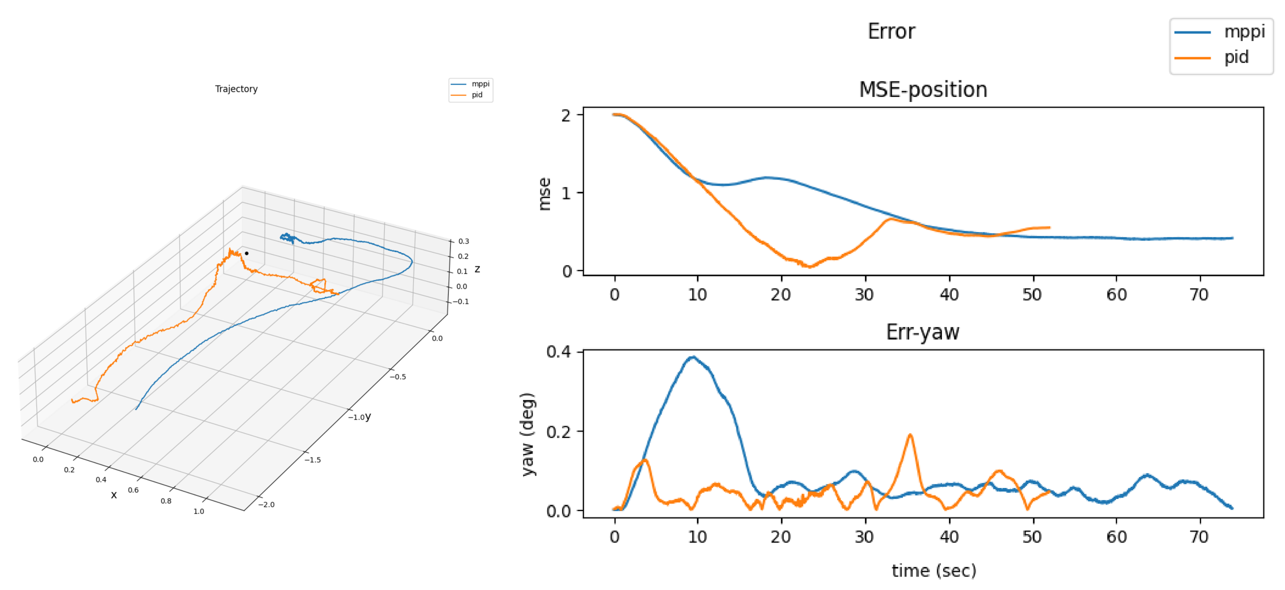
NN-learned model using bags of trajectories.



Despite the large error in the model, the controller, with it as the predictive model, was able to bring the AUV to the desired goal. The AUV was jittering at the goal position. This is due to the model-missmatch. This proves that MPPI can compensate for a huge model-missmatch but also that NN-MPPI is a viable solution for AUV control.

Company results

We tested the controller with the sponsoring company using an manually identified Fossen model described in Proctor's thesis [3].



The model miss-matches the ground truth as *Vaarst* added different sensors on the AUV. However, the (untuned) controller was able to successfully reach the goal. The operator also mentioned the higher stability along *Yaw*. Tuning the controller as well as adapting the model to the changed AUV would increase its performances even further.

Key benefits

- A model-based controller "only" needs to learn the dynamical model as the optimisation is performed online.
- The sampled-based approach doesn't require gradient computation and can thus use any type of forward model.
- The adaptation of the model can be performed asynchronously while the controller still operates.
- Should work with any AUV (and easily extend to almost-any robot) as long as there is proprioception.
- Can effectively control all degrees of freedom simultaneously, which is not the case for classic controllers such as PID.

citations

[1] G. Williams, N. Wagener, B. Goldfain, P. Drews, J. M. Rehg, B. Boots, and E. A. Theodorou, "Information theoretic MPC for model-based reinforcement learning," *Proceedings - IEEE International Conference on Robotics and Automation*, pp. 1714–1721, 2017, issn: 10504729. doi: 10.1109/ICRA.2017.7989202.

[2] T. Fossen, *Marine control systems: guidance, navigation and control of ships, rigs and underwater vehicles*. Springer, Dec. 2002, vol. 28, isbn: 82-92356-00-2.

[3] A. Proctor, "Semi-autonomous guidance and control of a saab seaeye falcon rov," Aug. 2014, p. 634, isbn: 9783540773406.

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