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M A S T E R ' S   T H E S I S
for
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Degree Electrical Engineering and Information Technology

Kernel Embedding for Particle Gibbs-Based Optimal Control

Problem description:

Bayesian learning-based control approaches are promising for safety-critical systems where physical modeling is time-consuming or impossible. A common problem in such systems is that not all states can be measured, resulting in the absence of a closed-form expression for the posterior distribution. However, particle Markov chain Monte Carlo (PMCMC) methods like particle Gibbs sampling can draw samples from the posterior distribution. These samples can be used to formulate a scenario optimal control problem (OCP), for whose solution probabilistic constraint satisfaction guarantees can be inferred [1]. However, representing the unknown dynamics using samples is exceedingly inefficient because many samples are required for a good representation. In addition, the scenario OCP must be solved repeatedly to infer probabilistic guarantees.

Kernel embedding is a promising alternative that allows the representation of unknown distributions with few samples, even if their parametric form is unknown. In recent years, this idea has been increasingly used for stochastic optimal control, among others, in [2] and [3]. A major advantage of these approaches is that the desired robustness level can be specified a priori and does not have to be determined by repeatedly solving the OCP.

This thesis thus aims to implement an optimal control approach that combines PMCMC methods for system identification with kernel embedding. Furthermore, the robustness of the proposed approach shall be analyzed, and the resulting algorithm shall be evaluated using simulations.

Tasks:

- Literature research on kernel embedding and PMCMC-based control
- Implementation of an optimal control approach that utilizes kernel embedding
- Robustness analysis of the proposed approach
- Numerical evaluation of the proposed approach

Bibliography:

[1] R. Lefringhausen, S. Srithasan, A. Lederer, and S. Hirche, "Learning-based optimal control with performance guarantees for unknown systems with latent states," *arXiv preprint*, 2023.

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[3] A. Thorpe, T. Lew, M. Oishi, and M. Pavone, "Data-driven chance constrained control using kernel distribution embeddings," in *Learning for Dynamics and Control Conference*, pp. 790–802, PMLR, 2022.

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(S. Hirche)