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Master Thesis

Residual model learning using action-conditional Recurrent Kalman Networks

Efficiently automating industrial assembly tasks such as cable plugging, shaft-hub insertion and printed circuit board mounting is of major interest to the robotics community and industry. In order to solve such tasks using approaches from planning, learning from demonstration, and/or model-based reinforcement learning, knowledge of the interaction dynamics is of critical importance.

The engineering challenge we would like to highlight here is dealing with the complex dynamics of robot arms, and in particular those dominant during slow and precise motions. It is observed that the performance of compliant control methods are limited by the system knowledge, and that traditional rigid-body models [1] are often insufficient. Recently, modeling approaches based on deep neural networks are proposed as alternatives, where e.g., Recurrent Kalman Networks (RKNs) [2] and its recent action-conditional extension [3] have shown very good performance. A well-known limitation of neural-network based models is the generalization to unseen situations, or situations where not much data is available during training; a matter that is much less apparent for traditional models that are parameterized in much fewer variables. To improve generalization it is therefore attractive to explore the combination of traditional and deep-neural-network-based models. One approach to this is to let the neural networks fit residual models and only focus on the effects not captured by the rigid-body dynamics models [4]. These effects may range from complicated friction effects to contact dynamics with the environment.

The topic of this Master's thesis is to explore the combination of ac-RKNs with traditional rigid-body dynamics models of robot arms with the scope of improving the steady-state accuracy of impedance controllers. Possible extensions can include improving dynamic tracking accuracy and modeling of the interaction dynamics with the environment.

Prerequisites

- Background in robotics and control.
- Experience with programming in Python.
- Experience with Tensorflow and/or PyTorch is a plus.
- Experience with ROS is a plus.

References

[1] C. D. Sousa and R. Cortesão, "Inertia tensor properties in robot dynamics identification: A linear matrix inequality approach," *IEEE/ASME Transactions on Mechatronics*, vol. 24, no. 1, pp. 406–411, 2019.

[2] P. Becker, H. Pandya, G. Gebhardt, C. Zhao, J. Taylor, and G. Neumann, "Recurrent kalman networks: Factorized inference in high-dimensional deep feature spaces," 2019, arxiv:1905.07357v1.

[3] V. Shaj, P. Becker, D. Buchler, H. Pandya, N. van Duijkeren, C. J. Taylor, M. Hanheide, and G. Neumann, "Action-conditional recurrent kalman networks for forward and inverse dynamics learning," 2020, arxiv:2010.10201v2.

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