Proceedings of Machine Learning Research vol 120:1–2, 2020

Data-driven Identification of Approximate Passive Linear Models for Nonlinear Systems

S. Sivaranjani SSEETHAR@ND.EDU
Etika Agarwal ETIKA.AGARWAL09@GMAIL.COM
Vijay Gupta VGUPTA2@ND.EDU
Department of Electrical Engineering, University of Notre Dame.

Abstract

In model-based learning, it is desirable for the learned model to preserve structural properties of the system that may facilitate easier control design or provide performance, stability or safety guarantees. Here, we consider an unknown nonlinear system possessing such a structural property - passivity, that can be used to ensure robust stability with a learned controller. We present an algorithm to learn a passive linear model of this nonlinear system from time domain input-output data. We first learn an approximate linear model of this system using any standard system identification technique. We then enforce passivity by perturbing the system matrices of the linear model, while ensuring that the perturbed model closely approximates the input-output behavior of the nonlinear system. Finally, we derive a trade-off between the perturbation size and the radius of the region in which the passivity of the linear model guarantees local passivity of the unknown nonlinear system.

Fig. 1 outlines the passive model identification approach. Learning a passive linear model (rather than a linearization) allows for a variety of distributed control designs that specifically leverage passivity (Tippett and Bao (2013); Agarwal et al. (2019); Agarwal et al. (2020); Sivaranjani et al. (2018)). A passive model can also be used to satisfy complex control specifications that cannot be achieved using only passivity indices learned from data. Finally, adopting the perturbation approach (rather than enforcing passivity constraints on standard system identification) significantly reduces computational complexity, allows for a wide choice of identification tools, and provides passivity guarantees on the original nonlinear system with controllers designed using the identified model.

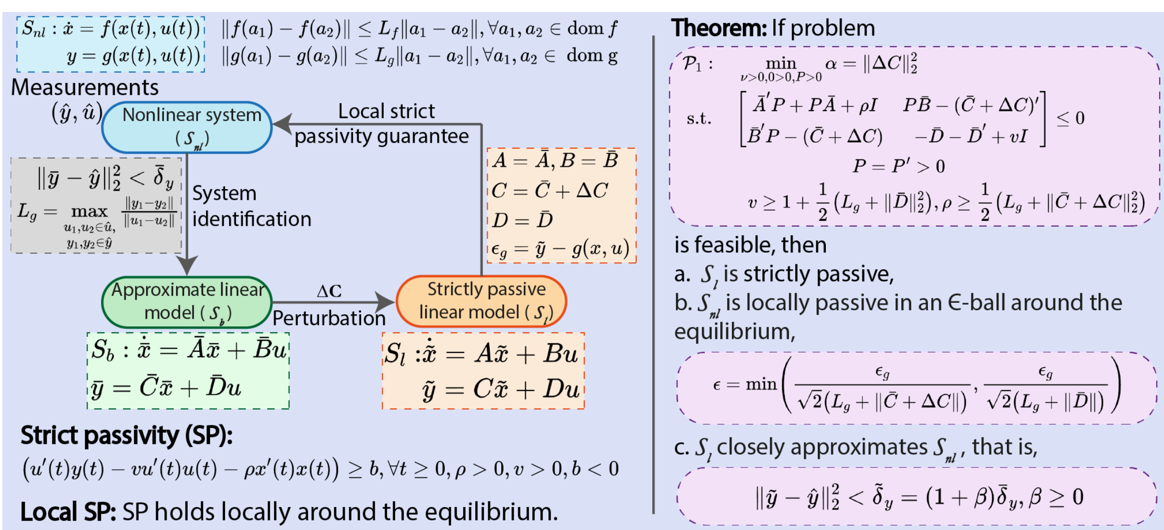

Figure 1: Overview of passive model identification.

Funding

The work of V. Gupta was supported by NSF grant CNS-1739295, DARPA grant FA8750-20-2-0502 and ARO grant W911NF1910483.

References

E. Agarwal, S. Sivaranjani, V. Gupta, and P. J. Antsaklis. Distributed synthesis of local controllers for networked systems with arbitrary interconnection topologies. *IEEE Transactions on Automatic Control*, pages 1–1, 2020. doi: 10.1109/TAC.2020.2990754. *arXiv:1902.10506*.

Etika Agarwal, S Sivaranjani, Vijay Gupta, and Panos Antsaklis. Sequential synthesis of distributed controllers for cascade interconnected systems. In *2019 American Control Conference (ACC)*, pages 5816–5821, July 2019.

S Sivaranjani, Etika Agarwal, Le Xie, Vijay Gupta, and Panos Antsaklis. Distributed mixed voltage angle and frequency droop control of microgrid interconnections with loss of distribution-pmu measurements. *arXiv preprint arXiv:1810.09132*, 2018.

Michael James Tippett and Jie Bao. Distributed model predictive control based on dissipativity. *AIChE Journal*, 59(3):787–804, 2013.