Manifold learning for data-driven dynamical system modeling ICASSP 2019 - Demo

The extraction of models from data (in a sense, the "understanding" of the physical laws giving rise to the data) is a fundamental cognitive as well as a scientific challenge. The demonstration we present revolves around a geometric/analytic learning approach capable of creating minimal descriptions of parametrically-dependent unknown nonlinear dynamical systems. This is accomplished by a data-driven extraction of useful intrinsic-state variables and parameters, in terms of which, one can empirically model the underlying dynamics. This approach follows recent trends in data analysis and signal processing, operating directly on observations, systematically creating accurate representations from data, without deriving models in closed-form and without any prior knowledge about the system dynamics. In particular, we present a kernel-based manifold learning approach, which learns the intrinsic geometric structure underlying the observations by capturing and exploiting the co-dependencies between the different dimensions of the data.

The proposed presentation is based on our recent paper (Yair, et al., 2017) and will include a live demonstration of the key capabilities of this method. Concretely, given high-dimensional, nonlinear, and multimodal observations of nonlinear dynamical systems, we will show in real time, that our method, without any prior knowledge, can provide meaningful low-dimensional representations, which: (i) accurately model the system, (ii) are invariant to the observation modalities, and (iii) facilitate system imitation and predictions.

The demonstration setup includes:

1. Nonlinear dynamical systems.
   For the purpose of demonstration, we will set up three prototypical dynamical systems: (i) a mass on a spring, (ii) a simple pendulum, and (iii) an elastic pendulum. The mass on a spring can be described using a single linear ordinary differential equation (ODE) and it has a closed-form solution with a single normal form. This system will be used for validation, i.e., for showing that known solutions and principles are indeed recovered empirically in a data-driven manner. The simple pendulum is slightly more evolved. This system can be described using a single *nonlinear* ODE and it does not have a known closed-form solution. However, in the regime of small swings, the system can be linearized, exhibiting a single normal form. We will show that in both regimes (linear and nonlinear), accurate normal forms can be recovered from observations. The third system, the elastic pendulum, can be described using two nonlinear coupled ODEs, which do not have a closed-form solution as well. This system will be used to demonstrate that our method is capable of recovering more than one normal form in the same agnostic manner.
2. Multimodal nonlinear acquisition of system observations.
   Our nonlinear observation function is a camera recording the dynamical systems in motion. To demonstrate the invariance to the observation modality and to show

that no image processing tools are used, the acquired video from the camera is randomly scrambled prior to the processing by the presented method.