Paper ID: 69089
student

IAF SPACE SYSTEMS SYMPOSIUM (D1)
Cooperative and Robotic Space Systems (6)

Author: Mr. William Parker
Massachusetts Institute of Technology (MIT), United States, wparker@mit.edu

NON-PARAMETRIC MODELING FOR STATE ESTIMATION FILTERING AND CONTROL OF AGGREGATE SPACECRAFT SYSTEMS

Abstract

For many emerging satellite tasks including space debris removal and on-orbit assembly and servicing, a spacecraft will need to grapple and manipulate objects with potentially unknown or uncertain properties. The resulting aggregate systems could potentially exhibit complex dynamics from flexible modes, propellant slosh, or dynamic geometry. While good models exist for describing such behavior, the challenge is in determining which model is appropriate when the system properties are not known a priori. Existing approaches for defining a dynamics model on-orbit typically involve presuming a parametric model structure (e.g. rigid body dynamics) and performing parameter estimation by observing the vehicle control inputs and state history over an informative dynamical trajectory. The parametric model structure is beneficial because system dynamics are succinctly described by some relevant parameters which are computationally inexpensive to estimate. The limitation is that this modeling technique is unable to capture any dynamics beyond those which are presumed in designing the model structure. In contrast to parametric modeling, non-parametric models built with machine learning techniques are much more expressive and are able to capture arbitrarily complex vehicle dynamics. Indeed, recent advances in machine learning and artificial intelligence have introduced new methods that are capable of building regression models with an awareness of both the aleatoric and epistemic uncertainty in the measurements and model, respectively. Gaussian Process Regression (GPR), Bayesian Neural Networks (BNN), and Deep Evidential Regression (DER) allow a spacecraft to learn dynamics through observing an informative trajectory of control inputs and sampled states. These methods also track and report their uncertainty, which can decide when a model should be trusted for performing critical mission tasks. State estimation and control are operations that frequently rely on accurate process models, but these process models have historically been analytical and parametric, requiring a priori knowledge of the system. In this work, uncertainty-aware learned non-parametric dynamics models are used for state estimation filtering and model predictive control (MPC). A non-parametric unscented Kalman filter is developed and applied to perform state estimation for a flexible multi-body satellite system. Similarly, a non-parametric MPC framework is constructed which propagates dynamics forward to ensure constraint satisfaction. Learning-based methods are shown to be favorable compared to parametric modeling methods for both the filtering and control applications in simulation. The tools developed in this work are generally applicable and potentially useful for non-parametric learning and control of complex, uncertain systems with no a priori knowledge.